Modelling Landscape-scale Species Response to Agri-Environment Schemes

Final project report, March 2021

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UKCEH project number 07678
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Contents

Executive summary

Agri-environment schemes (AES) are the most significant environmental policy delivery mechanism in England, and include the conservation of biodiversity as a key objective. Provisional results from the ongoing *Landscape-scale species monitoring of AES* (LandSpAES) baseline field survey have shown some positive responses of mobile taxa to AES gradients at local ($1km^2$) or landscape ($3 \times 3km$) scales. However, it is not known whether these provisional results might be more broadly applicable outside the regions surveyed in the LandSpAES project, i.e. in other regions, or nationally.

Here, we present the findings of an analytical project to explore the use of national Citizen Science (CitSci) scheme data, to investigate whether similar relationships with AES gradients would be found at a national scale in CitSci data to those shown with LandSpAES data, and whether integrated modelling was possible with combined CitSci and LandSpAES datasets. The design of LandSpAES has high power to detect AES effects, including the independent testing of the local and landscape AES gradients, but is restricted to six regions. The national CitSci are more representative of England as a whole, but have not been designed to detect AES effects.

The **aim** of this project was to determine whether the provisional taxon responses to the AES gradients found in the LandSpAES project could be detected at a national scale using CitSci scheme data.

To achieve this aim, three **key questions** were addressed through the analytical work:
1) Can addition of covariates account for environmental variation between survey squares in each dataset, to improve the comparability of AES gradient effects between LandSpAES and CitSci schemes?
2) Do the CitSci scheme datasets show similar relationships between taxa responses and the AES gradients, to those found with the LandSpAES data?
3) Can integrated approaches to combining datasets be used to jointly model CitSci and LandSpAES data, and does integrated modelling reduce uncertainty in quantifying the effects of AES gradients on taxa responses at a national scale across England?

Approach

- The AES gradient approach developed for the LandSpAES project was used to calculate local and landscape AES gradients for every 1km grid square in England, using recently updated data on the uptake of AES management options.
- Six CitSci schemes were scoped to investigate their suitability for comparison with the LandSpAES project. Schemes that have a good quantity of data, good coverage of AES gradients and absence of confounding relationships with other variables are most likely to provide robust estimates of AES relationships that can be compared with LandSpAES data. The CitSci datasets considered here are long-term monitoring schemes designed to look at change in populations over time, and were not designed to test the effects of AES gradients, unlike the LandSpAES project. The scoping work is specific to the requirements of this project, so it does not reflect the broader

strengths or weaknesses of the CitSci schemes, or their suitability for other potential analytical work.

- The standardized criteria that were assessed in the scoping were: quantity of data between 2017 and 2019 (number of sites and number of surveys per site); correlations between the local and landscape AES gradients; correlations between the AES gradient and other habitat variables (area of arable, area of grassland, area of semi-natural habitats, habitat diversity); coverage of the CitSci scheme sites (whether sites covered most of England, coverage of upland / lowland areas, any regional bias in the AES gradients); and differences in the survey design and monitoring protocol between the CitSci scheme and the same taxa on the LandSpAES project.
- Response variables were calculated for five taxa (butterflies, bumblebees, hoverflies, solitary bees, birds) using both LandSpAES and CitSci data. For each taxon, three headline community response variables (species richness, Shannon diversity index, total abundance) were used in the analytical work. For birds, additional response variables were calculated: the abundance and species richness of Farmland Bird Index, the abundance of red list species and the abundance of each of six exemplar farmland species.
- A core model to assess AES effects was constructed for each response variable from LandSpAES and CitSci data, which included the local and landscape AES gradients, a fixed effect of year and any other scheme-specific terms needed to account for within-scheme variation in sampling effort.
- Data for 28 environmental variables were sourced, which included information on coverage of broad habitat categories, soil, aspect, slope, elevation, rainfall and temperature. Ordination techniques (Principal Component Analysis or PCA) were used at the 1km square level, in order to define ordination axes that reflected the majority of variation in these environmental variables for inclusion in models. The aim of including these PCA axes was to account for variation in response not due to AES and facilitate comparison of AES effects between LandSpAES and CitSci datasets.
- PCA axes were selected for inclusion in the models of AES gradient effects, for each of the taxa response variables. The first two PCA axes were included in all models. Addition of further PCA axes was contingent on improving the model fit, and it was possible to fit more PCA axes to the larger datasets than the smaller datasets.
- For each response variable, the effects of the local and landscape AES gradients, and the interaction between them, were determined separately for the LandSpAES and CitSci datasets. In order to determine whether the two datasets showed similar relationships between taxon responses and the AES gradients, coefficients were compared from the two models, both in terms of the magnitude and direction of the relationship, and using formal tests of coefficient similarity (z-tests).
- Integrated models were fitted and evaluated for those response variables where good evidence was found that relationships with the AES gradients were similar between LandSpAES and CitSci datasets. The potential advantage of integrating data is that more precise estimates of effects may be obtained across multiple datasets, and these estimates have wider relevance and representativeness, compared to models using single datasets. In the context of AES gradient effects, if an integrated model is

appropriate across LandSpAES and a CitSci dataset, the results can be considered as representative of a larger, potentially national, scale.

- The integrated modelling used a framework that allowed multiple elements of survey design or protocol to vary between the datasets, without having to attribute differences in species response between datasets to particular survey elements. For the majority of response variables, the integrated models allowed the LandSpAES and CitSci datasets to have different average species responses (i.e. different intercepts), but assumed relationships with the AES gradients were identical across the datasets. Attempts were made to fit more complex models which allowed the relationships with the AES gradients to also vary between the datasets, but in most cases these more complex models could not be used due to convergence errors.
- The integrated models were evaluated using three metrics which capture slightly different elements of model performance, and the precision of the estimated AES effects. The median absolute error (MAE) and root mean square error (RMSE) were used to understand absolute error of the model. The coefficient of variation (CV) calculates error relative to the mean response. Precision around AES estimates was captured by the standard errors - the smaller the standard error the higher the precision, and therefore the more confidence we have in the AES gradient trends.

Key findings

Scoping of CitSci schemes

- Six CitSci schemes were included in the scoping, five insect schemes and one bird scheme (the Breeding Bird Survey or BBS). The butterfly CitSci schemes and in particular the BBS had substantial amounts of data, with between 500 and 2300 sites surveyed a year. Approximately 30 sites a year were surveyed on the smaller UK National Pollinator Monitoring Scheme (PoMS) and the Rothamsted Insect Survey for moths (RIS moths). The BeeWalks scheme was intermediate, with 160 – 241 sites surveyed each year. For comparison, the LandSpAES project surveys 54 1km squares each year.
- For all the CitSci schemes, correlations between the local and landscape AES gradients were stronger than for the LandSpAES project, which was designed for independence of these gradient scales. However, for five of the CitSci schemes the correlation strengths were moderate (0.62 – 0.67), while for the sixth scheme a strong correlation (0.74) was found.
- Correlations between the AES gradients and habitat variables were weak or absent (less than ± 0.4) in most cases for the majority of the CitSci schemes, suggesting that the AES gradient effects are not confounded with other habitat variables in the models developed below. For PoMS, moderate negative correlations were found between the area of arable land and both AES gradients (-0.42, -0.47), and some moderate positive correlations between the each of the AES gradients and both area of grassland (0.43, 0.35) and area of semi-natural habitats (0.24 – 0.61). For the RIS moth data, some moderate positive correlations were found between the AES gradients and the area of grassland (0.43, 0.34) and area of semi-natural habitats (0.3 – 0.72). For these two CitSci datasets, it may therefore be harder to separate the effects of AES gradients from those of underlying habitat.

- Most of the CitSci schemes scoped had reasonable national coverage across England, although inevitably there were more gaps for the smaller schemes with fewer sites. No evidence of regional bias in AES gradient coverage was found.
- Many of the CitSci schemes had similar methods (monitoring protocols) to those used in LandSpAES, which was a deliberate part of the LandSpAES project design. There was a split between three CitSci schemes and LandSpAES that are designed to survey a 1km grid square, for which there is high confidence that the AES gradient and covariate (habitat and environmental variables) values attributed to 1km grid squares will match the survey units. Three of the CitSci schemes were not designed to survey 1km grid squares: for these the transect route centroid or the trap location were used to allocate each site to a 1km grid square, but there is lower confidence in the spatial matching of AES gradient and covariate values.
- Five of the CitSci schemes were used in the analytical work, following the scoping. The RIS moth scheme was not included, due to the strong correlation between the AES gradients, moderate correlations with habitat variables, and quite different monitoring protocols to the LandSpAES project. While PoMS was included in analytical work, the moderate correlations found between the AES gradients and some habitat variables reduce confidence in any AES effects shown in the modelling.

Accounting for environmental variation

- The first two ordination (PCA) axes, calculated to summarise environmental variation, related to climatic variables (mainly rainfall) and habitat variables (area of arable vs. area of improved grassland) respectively. 26% and 12% of variation was explained by the first and second PCA axes, respectively, and these were included in the models for every response variable and dataset. A further one to 26 PCA axes were added to each model, with fewer PCA axes added to the smaller datasets, and most to the largest (BBS) dataset.
- Using PCA axis scores in the models caused few differences in the detection of AES gradient effects on taxa responses in models, compared to previous models of LandSpAES data which had used a regional blocking random term for analyses. For the butterflies, some additional positive effects of AES gradients were found as a result of using the PCA axis scores. This supports the general approach in this study to describe variation between survey squares in terms of land cover and other environmental variables.

Modelling of AES gradient effects separately for each dataset

- Taxa responses varied in similarity between the LandSpAES data and the different CitSci datasets. For some responses (e.g. butterfly richness) there was strong evidence of highly similar relationships between LandSpAES and CitSci schemes, in relation to the AES gradients. For other responses (e.g. abundance of Red List birds), there was strong evidence of highly dissimilar relationships with AES gradients between the LandSpAES and CitSci datasets.
- For bird assemblage response variables, there was little evidence that similar effects of the AES gradients were found in the BBS and LandSpAES datasets. For abundance of each of the six exemplar farmland bird species, there were more similarities between the BBS and LandSpAES datasets, in relation to the effects of AES

gradients, than for the headline community responses. However, large number of zeros in the single species data let to large confidence intervals. Despite the larger sample size in BBS, there were some responses for which a significant relationship was observed in LandSpAES but not in the BBS. It is possible that relationships between bird responses and AES gradients in BBS may be dominated by the large number of squares with low AES gradient values, and that the structured design and more intensive data collection in LandSpAES delivered greater analytical power.

- For butterflies, there was good evidence that the effects of AES gradients found in the LandSpAES data were also present in the CitSci scheme datasets. The WCBS scheme was more similar to the LandSpAES dataset, in terms of AES effects on butterfly species richness and total abundance, than the UKBMS dataset was. Significant positive relationships with either the local or the landscape AES gradients were found for butterfly abundance, diversity and species richness.
- For bumblebees surveyed along transects, no significant effects of the AES gradients on bumblebee species richness, diversity or total abundance were found in either the BeeWalks or the LandSpAES data. The non-significant relationships with AES gradients were broadly similar across the two datasets, especially for species richness.
- For the pan trap pollinator surveys, there was little indication of similar responses to the AES gradients between the PoMS and LandSpAES dataset, for the majority of bumblebee, solitary bee and hoverfly responses. The only exception to this was solitary bee abundance, where the relationships with AES gradients were similar enough for integrated modelling. Negative relationships were shown between the AES gradients and some hoverfly and solitary bee response variables in the PoMS data, but not the LandSpAES data. As discussed above, the AES gradients were moderately confounded with some habitat variables at PoMS squares, perhaps due to the small number of sites currently surveyed, which may have driven these negative relationships.

Integrated modelling and conclusions

- Relationships were found to be similar enough to attempt modelling datasets jointly for nine out of 27 response variables, suggesting a majority of responses did not show similar relationships. However, the distribution of similar responses varied between taxonomic groups and survey methods, with all butterfly and bumblebee (transect surveyed) responses being similar between the LandSpAES data and CitSci schemes. By contrast, only one out of nine insect response variables from pan trap data that were tested were found to be comparable between LandSpAES and PoMS, and none of the pan trap bumblebee responses were comparable.
- Integrated models provided a consistent reduction in uncertainty (based on lower MAE and RMSE and similar CV) and showed a comparable response to that found on LandSpAES for five out of nine response variables where integrated models were trialled (butterfly richness, butterfly abundance, bumblebee richness, bumblebee abundance, solitary bee abundance). Integrated models were suitable for reducing uncertainty in quantifying AES gradient effects on taxa responses where there was very strong evidence of similar relationships between the LandSpAES and CitSci datasets.

- For the five response variables where integrated models resulted in reduced uncertainty and a comparable response to LandSpAES, significant positive main effects of one or both AES gradients were found using the integrated model for two of the response variables (butterfly richness and butterfly abundance). There was no evidence of a significant relationship with AES gradients for the two bumblebee response variables or solitary bee abundance.
- The majority of response variables were either not suitable for integrated modelling in this context, or the integrated modelling did not reduce uncertainty. Not all CitSci schemes that were scoped were included in the analytical work, and for one that was included it was not possible to entirely separate the effects of AES gradients from those of other habitat variables. In addition, for the larger CitSci schemes it is possible that greater sampling density at the low end of AES gradients may have driven the lack of relationships found with the gradients. All these factors emphasize the importance of monitoring projects, such as LandSpAES, that are carefully designed to maximize the detection of AES effects and to ensure independence from other potential confounding factors. The CitSci schemes assessed here were designed to monitor trends over time, rather than spatial variation in relation to AES.
- Data and results reported here from the LandSpAES project are provisional, as a fourth year of baseline field survey is currently underway. Final reporting will include more detailed analyses of trait group and species response variables than those reported here, and there is some indication that abundance of certain trait groups may be affected by the AES gradients, while the total taxon abundance is not. Due to the findings here being mainly for responses that are headline community-level variables, and the LandSpAES baseline dataset being incomplete, it might be worthwhile repeating some or all of this analytical work in more detail after the LandSpAES field survey is completed.

Summary The detailed analyses used in the project were carefully designed to assess differences between CitSci and LandSpAES datasets that might affect observed relationships with AES gradients, to account for variation due to other environmental variables, to explore similarity in relationships between response variables and the AES gradients across comparable datasets, to attempt integrated modelling only where this was appropriate from the preceding work, and to evaluate the effectiveness of the integrated modelling. There was variation between taxonomic groups and the CitSci schemes, in relation to whether the LandSpAES and CitSci datasets showed similar relationships between taxon responses and the AES gradients. This variation may be due to differences between the CitSci schemes in terms of size, design or distribution along the AES gradients, or regional variation in relationships with AES. For nine out of 27 responses, across five CitSci datasets, comparisons were sufficiently similar that it was possible to jointly model LandSpAES and CitSci data. Integrated models reduced uncertainty in relationships with AES gradients and showed a comparable response to that found on LandSpAES in five out of the nine integrated models. The integrated modeling showed that two of these five response variables had a positive, significant relationship with either local or landscape AES gradients, while for the other three responses no significant effects of the AES gradients were found. The successful joint modelling and reduced uncertainty for these five response variables provides evidence that some AES gradient effects, observed using highly structured and targeted sampling in six

regions in LandSpAES, are sufficiently similar to those that are detectable in national CitSci data, thus supporting reliable models at a national scale. However, these responses were a minority of those tested, suggesting that CitSci schemes cannot be assumed to provide equivalent inference to a specifically designed study.

1. Introduction

1.1 Rationale and background to the project

Agri-environment schemes (AES) are the most significant environmental policy delivery mechanism in England, and include the conservation of biodiversity as a key objective. Monitoring of AES is necessary to determine their impacts on target species, and on wider biodiversity. The ongoing *Landscape-scale species monitoring of AES* project (LandSpAES, Natural England project reference LM0465) is establishing a baseline against which the effects of agri-environment scheme gradients on the responses of key mobile taxa can be assessed at two spatial scales.

Provisional analyses of three years data from LandSpAES indicate that some taxa have shown some positive responses to the AES gradients in the surveyed regions (Section 1.4 below). However, it is not known whether these provisional results might be more broadly applicable outside the regions surveyed in the LandSpAES project, i.e. in other regions, or nationally. In this current project, the AES gradient approach developed for the LandSpAES project (Staley et al. 2016) was applied more widely to sites across England where species resolution data is available from several long standing Citizen Science (CitSci) monitoring schemes. Relationships between key taxa response variables and the AES gradients were explored for each CitSci scheme that was included in the analytical work. Integrated analyses were then conducted with combined LandSpAES and CitSci data, for some response variables. The broad aim of this project was, thus, to explore whether the provisional taxa responses to AES gradients found in the LandSpAES project, which was designed to maximise the potential to detect AES gradient effects, could be detected at national scales using CitSci scheme data.

There are several key differences in the design of LandSpAES (Section 1.2 below) and the CitSci schemes. The design of LandSpAES has high power to detect AES effects, whilst the national schemes are more representative of England as a whole. Here, where possible, design differences were accounted for in the analytical approaches, for example through the inclusion of environmental variables to account for variation in taxon responses that do not relate to the AES gradients. However, many of the differences in design between the LandSpAES project and CitSci schemes could not be accounted for analytically. Where the relationships between response variables and AES gradients differ between the datasets, potential reasons for those differences are discussed in this report, but it was not always possible to determine the cause of these differences.

The analytical methods used here are largely exploratory. Hence, the analyses consider whether, for example, environmental variables can be successfully included in models to account for non-AES variation, and whether integrated modelling is possible for any response variables, given the differences between LandSpAES and CitSci designs. In addition, data collection for the LandSpAES multi-year baseline survey is ongoing, so the findings discussed in this report with respect to LandSpAES are provisional. Due to this, the results presented here should be considered as demonstrating the use of the analytical approaches developed in this project to test whether taxa responses to AES gradients demonstrated on LandSpAES may be shown at wider, national scales. They should not be interpreted as final analyses of taxa responses to the AES gradients, either for the LandSpAES baseline or the CitSci schemes.

1.2 Summary of the survey design for the *Landscape-scale species monitoring of AES (*LandSpAES) project, and potential for extrapolation to unsurveyed areas

An approach to calculating AES intervention gradients was developed previously (Staley et al. 2016), and applied for survey square selection within the LandSpAES project. AES gradient scores were calculated from a combination of AES option uptake data, an evidence score for each option in relation to resources and habitat provided for target taxa (determined from an evidence review) and the payment given for each option (to upweight arable options covering small areas that provide concentrated resources for target taxa, e.g. pollen and nectar mix). This resulted in gradients of AES management known to affect the key taxa, and excluded options that target other objectives (e.g. water protection, educational access).

For the LandSpAES design, we showed that a single approach to quantifying relevant AES management interventions and selecting study sites could be used for four different taxa / functional groups (Staley et al. 2016). Taxon-specific AES gradients were calculated using evidence scores that were specific for each taxon or functional group. Average AES gradients were found to correlate positively with each taxon-specific gradient, supporting the co-location of monitoring across birds, butterflies and pollinating insects. This allows any variation shown between the responses of taxa to the AES gradients to be attributed to differences in their underlying ecology, rather than potentially being confounded with differences between survey sites or study design. This co-location of monitoring used in LandSpAES allows a broad assessment of AES gradient effects on biodiversity.

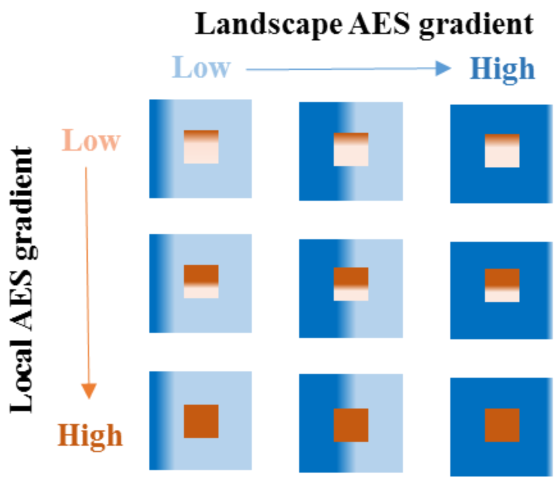

Figure 1.1 Contrasting gradients of taxon-relevant AES intervention at local and landscape scales, split into three classes. The local gradient is represented by shading from cream (low) to brown (high) in the focal 1km squares in which mobile taxa will be monitored, and the landscape gradient by pale blue (low) to dark blue (high) in the surrounding landscape (3 × 3km) units.

AES gradients were calculated at two spatial scales, a local scale defined as a 1 × 1km square, and a landscape scale as the surrounding eight 1km squares, i.e. a 3 × 3km annular landscape unit. While mobile organisms will move outside the landscape units, especially when dispersing or migrating, the majority of foraging journeys for any given population are within 3km (Carvell et al., 2012; Knight et al., 2005; Siriwardena, 2010; Siriwardena et al., 2006), and so populations are likely to be affected most by factors within these local and landscape scales. Once the two AES gradients were calculated, survey squares were selected to fill the cells in a matrix of orthogonal AES gradients (Figure 1.1), through a random selection process, which was weighted to increase the chance of each cell being filled in the matrix (Staley et al. 2016).

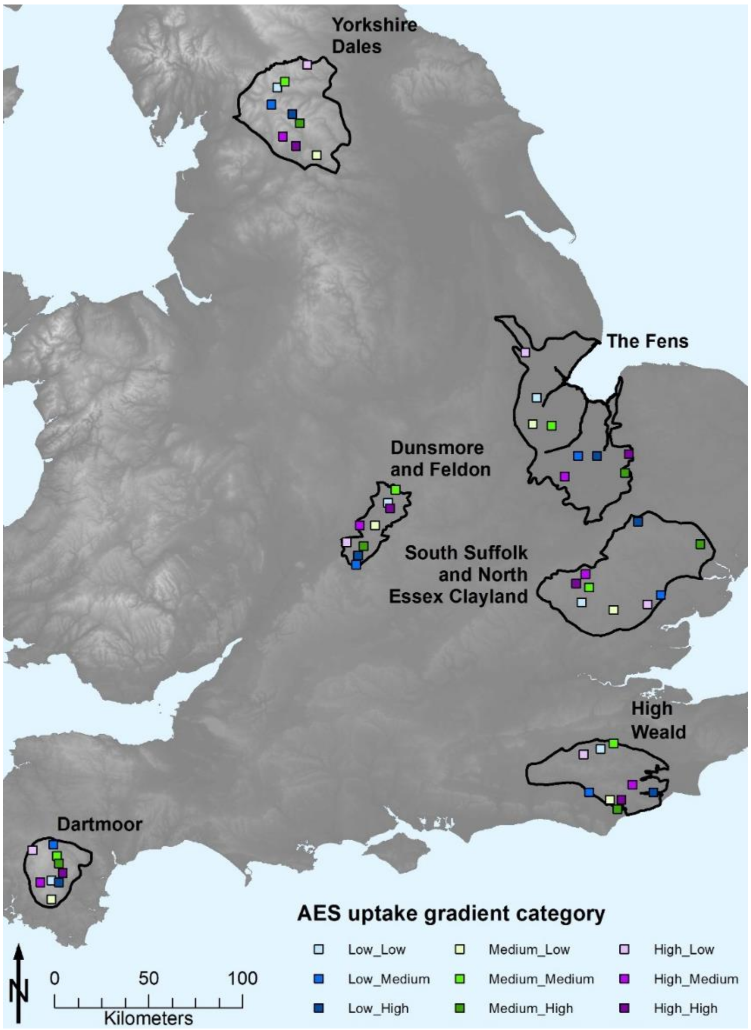

Figure 1.2 Six NCAs surveyed for the LandSpAES baseline from 2018. The four lowland NCAs were also surveyed in 2017.

National Character Areas (NCAs) are regions with cohesive landscape characteristics, and were used as blocks in which to group survey squares. Survey squares along these two AES gradients, within the contrasting matrix, were randomly selected within NCAs. Background habitat variables (habitat diversity, area of semi-natural habitat and area of arable lands) were shown not to relate strongly to the AES gradients, within each NCA.

Three years of survey data have been collected on butterflies, moths, bumblebees, solitary bees, hoverflies, birds and bats at the 54 survey squares grouped within six NCAs (Figure 1.2). These surveys have all been conducted by trained, professional surveyors, with proven expertise in the identification of the taxa they record on the project. A final, fourth year of baseline data collection is ongoing, to be completed by autumn 2021. Further details of the rationale underlying the LandSpAES survey design are in Staley *et al.* (2016).

The LandSpAES project described above has high power to detect the effects of the AES gradients on taxon responses, due to three aspects of the design. Firstly, survey squares represent the full range of the AES gradients in each NCA region. Secondly, survey squares were selected across a matrix of orthogonal local and landscape AES gradients (Figure 1.1), as described above. The selection of survey squares orthogonal gradients ensures that the effects of local vs. landscape AES gradients on taxon responses can be determined independently of each other, and also allows the interaction between the local and landscape AES gradients to be tested. Thirdly, the AES gradients were shown to be largely independent of background habitat variables within LandSpAES, through grouping squares within homogenous NCAs. If the survey squares had been selected along national AES gradients, it is possible that the gradients would have correlated with background habitat or environmental gradients, and the AES gradient effects could not have been distinguished from other variables. These elements of the LandSpAES design give us high confidence that the relationships observed with AES are unbiased, and independent of other landscape characteristics.

However, results from the LandSpAES project may not be representative at larger spatial scales, or nationally. There is a trade-off between a design that is controlled to maximise contrast in the variables of interest (AES gradients) through a pseudo-experimental approach, such as that used for LandSpAES, and one that is designed to be nationally representative. NCAs are defined as homogenous landscape areas that are qualitatively different from each other, and so results from the small group of six NCAs that are being surveyed on LandSpAES may not represent the wider populations of NCAs across England.

The provisional analyses of LandSpAES data, which are summarised in Section 1.4 below (and the planned final analyses), included the NCA as a random term in the modelling, to account for the grouping of survey sites within each of the six NCAs and the variation in background environmental (habitat and climatic) variables between NCAs. A preliminary investigation of predicting to unsurveyed areas from the LandSpAES provisional analyses, based solely on the AES gradient values (marginal predictions- as it was not possible to estimate an 'NCA effect' for unsurveyed NCAs) resulted in predictions that had very high uncertainty and low confidence in the results.

1.3. Methodological development to facilitate exploration of AES gradient effects in areas not surveyed under LandSpAES

In order to reduce the uncertainty in determining whether AES gradient effects could be detected in areas not surveyed under LandSpAES, this project investigated the inclusion of environmental variables in the analyses (Sections 4.2 and 4.3 for details). By replacing the 'NCA effect' with these environmental variables, we aimed to facilitate the use of additional, national scale data to explore relationships with AES gradients in areas not surveyed under LandSpAES, on the basis that the environmental variables are available for all 1km squares in England.

In order to explore whether these similar relationships could be detected in areas that were not surveyed under LandSpAES, this project used monitoring data that were collected in national CitSci schemes to model AES effects on taxa response variables. If similar relationships were found with AES gradients in the CitSci data, this would suggest that the relationships observed in LandSpAES were representative nationally. However, if differences were found in the relationship between taxa and AES gradients between LandSpAES and CitSci data, this could be due either to differences in design, methodology, confounding factors or sensitivity between the datasets, or to the LandSpAES relationships being restricted to the surveyed areas. We investigated the potential for CitSci schemes to provide comparable data to LandSpAES through initial scoping, and then tested whether similar relationships with AES gradients could be observed in CitSci datasets.

Finally, we investigated the potential for integrated approaches to be helpful in reducing uncertainty in quantifying relationships between taxon responses and the AES gradients, compared to models based only on the LandSpAES data. Integrated modelling allows multiple datasets, which may be collected in different ways, to be combined in a single model. This approach has been applied successfully in multiple fields, including modelling species distributions (Isaac *et al.*, 2020) and temporal trends in vegetation (under the UKCEH-Defra partnership). Integrated models can also be used to jointly estimate covariate effects for the selected response variables, by using both data sources to inform the parameter estimates (hence effect size; e.g. Siriwardena et al. 2017). Integrated models enable estimation of consistent AES gradient effects across datasets and may provide reduced uncertainty compared to modelling with LandSpAES data alone.

1.4 Summary of provisional results from three years of LandSpAES data

As the LandSpAES field survey is ongoing, provisional analyses to date have focused on community-level response variables (species richness, diversity and total abundance of taxa), which have been analysed each year for annual reporting. Several of the taxa monitored have shown positive relationships with either the local or the landscape AES gradient.

With three years of data, a provisional positive relationship between total butterfly abundance and the landscape (3 × 3km) AES gradient has been shown. Bumblebees also showed a positive relationship between abundance and the local ($1km^2$) gradient, though it was restricted to certain trait groups of bumblebees (those with a mid-length tongue). Moths had a positive relationship with the landscape AES gradient, both in terms of their total abundance and species richness. There were no clear relationships between AES gradients and the other insect taxa surveyed (hoverflies, solitary bees), from provisional analyses with three years' data. The landscape AES gradient also had a provisional positive relationship with bird species richness, in both summer and winter.

The provisional results summarised above are from analyses carried out in early 2020, and used AES gradients at the landscape (3 × 3km) scale that had been calculated in 2017, as more recent AES option uptake data were not available at the time. For the analyses reported here in the current project, and the planned final analyses of LandSpAES data (once the last year of field survey is complete), updated landscape AES gradients were used, to reflect the AES option uptake for each year of species data. For birds, further refinement of the species sets included in community variables has also been conducted. Due to these differences, the provisional LandSpAES results above are not directly comparable to the modelling outputs for the current project, but do provide some background context to the work reported here. In addition, more detailed trait and species-based analyses are planned for final analyses of the LandSpAES baseline data, so final reporting for LandSpAES will be more detailed, and may be more sensitive to the detection of AES effects. All analyses completed to date have looked at variation in relation to AES across space rather than change over time, which could be addressed through future re-survey.

1.5 Aim and key questions

1.5.1 Aim

To investigate the feasibility of spatially modelling the responses of mobile species to AES gradients in areas that were not surveyed for this purpose, building on the datasets collected during LandSpAES, through a) explaining spatial variation with additional environmental variables and b) exploring the potential to test and integrate citizen science datasets through joint modelling approaches.

1.5.2 Key questions to answer in this project:

1) Can addition of covariates account for environmental variation between survey squares in each dataset, to improve the comparability of AES gradient effects between LandSpAES and CitSci schemes?
2) Do the CitSci scheme datasets show similar relationships between taxa responses and the AES gradients, to those found with the LandSpAES data?
3) Can integrated approaches to combining datasets be used to jointly model CitSci and LandSpAES data, and does integrated modelling reduce uncertainty in quantifying the effects of AES gradients on taxa responses at a national scale across England?

2. Data collation and calculation of AES gradients

2.1 Data collation

The datasets used in this project can be split into those providing species data and those providing covariates. We identified five key citizen science (CitSci) schemes that collect species data on taxonomic groups surveyed as part of LandSpAES (Table 2.1). Throughout the project we considered the Wider Countryside Butterfly Survey (WCBS) separately from the other UK Butterfly Monitoring Schemes (UKBMS) data due to differences in design (see Section 3.2 for further detail). We also sourced data from the ongoing LandSpAES project from 2017, 2018 and 2019 surveys. For all species datasets we restricted the data used in this project to 2017-2019 to match the temporal extent of the LandSpAES data.

Table 2.1.1. List of datasets used in this project providing species data.

Species dataset	Taxonomic groups covered	Owner/supplier	License terms
UK Butterfly Monitoring Schemes (UKBMS) including Wider Countryside Butterfly Survey (WCBS)	Butterflies	UKBMS partnership	Open Government Licence
BTO/JNCC/RSPB Breeding Bird Survey (BBS)	Birds	BTO	Data held by BTO
BeeWalk	Bumblebees	Bumblebee Conservation Trust	Publically available
UK Pollinator Monitoring Scheme (PoMS)	Bumblebees Solitary bees Hoverflies	UKCEH	Open Government Licence
Rothamsted Insect Survey: light-trap network	Moths	Rothamsted Research	Data held by Rothamsted Research
Landscape-scale species monitoring of AES (LandSpAES)	Birds Butterflies Bumblebees Solitary bees Hoverflies Moths	UKCEH / BTO / NE	Currently held by project team, will be publically available after the project ends

We also obtained a range of datasets providing information on environmental covariates for use in species modelling (Table 2.2).

Table 2.2. List of datasets used in this project providing covariate data.

Covariate dataset	Citation	Owner/supplier	License terms
National Character Areas		NE	Open Government Licence
Countryside Stewardship & Environmental Stewardship scheme options (England)		NE	Open Government Licence
Land Cover Map vector dataset for Great Britain (2015, 2017, 2018, 2019)	Rowland *et al*., 2017, Morton *et al*., 2020a, 2020b, 2020c	UKCEH	Licensed by UKCEH
UKCEH Land Cover *plus*®: Crops vector datasets (2015, 2016, 2017, 2018, 2019)		UKCEH	Licensed by UKCEH
Integrated Hydrological Digital Terrain Model (IHDTM)		UKCEH	Licensed by UKCEH
Soil Parent Material 1km resolution		BGS	Open Government Licence
Climate, Hydrology and Ecology Research Support System meteorology dataset for Great Britain (CHESS-met; 2011-2015)	Robinson *et al*. 2020	UKCEH	Licensed by UKCEH
Woody Linear Features Framework	Scholefield *et al*. 2016	UKCEH	Licensed by UKCEH
Less Favoured Areas (LFA)		Defra	Open Government Licence

2.2 Calculation of AES gradients

AES gradients at both local (1km^2) and landscape (3 × 3km) scales were calculated for all 1km squares in England, following the approach developed for AES gradients for LandSpAES (summarised in Section 1.2 above, for further details see Staley et al. 2016). We used AES option uptake data from the Natural England Open Data Geoportal, for both Environmental Stewardship (ES) and Countryside Stewardship (CS). We incorporated data from two time periods: 1) data obtained for the LandSpAES project in 2017, 2) the most recent data from December 2020, in order to capture any changes in AES uptake over the time span of the LandSpAES project (2017-2020), especially caused by the cessation of ES and the establishment of new CS agreements. Within each dataset there is information on each option's start and end date, so by using these data we were able to generate an annual gradient score for each of 2017, 2018, 2019 and 2020, for each 1km grid cell.

Gradient scores were calculated as in LandSpAES (Staley et al. 2016). The sequence of matching options to a 1km grid cell is illustrated in Figure 2.2.1. Firstly, each 1km grid cell was intersected with the Rural Land Registry/Land Parcel Information System (RLR/LPIS) parcel boundaries, to identify all land parcels that may potentially contribute options to the cell's score (Figure 2.2.1, panel 1). The parcel codes of all RLR/LPIS land parcels within the cell were then matched to the AES uptake data, identifying all options within these land parcels (Figure 2.2.1, panel 2). We also performed a spatial intersection of option coordinates to identify where options were recorded within parcels despite not matching the parcel code, potentially due to parcel codes being updated, split or merged (Figure 2.2.1, panel 3). The quantity of the option (usually area, but also length, or number of features) was then multiplied by the proportion of the associated land parcel which intersected the square Figure 2.2.1, panel 4), giving an estimate of the quantity of the option lying within the square and thus contributing to its total score. Finally, we matched the 1km grid reference of the cell to the grid references in the AES uptake data, to identify options within the cell which could not be associated with an RLR/LPIS parcel via parcel code or via intersection of spatial coordinates (Figure 2.2.1, panel 5). These were mostly agreement level options or, in rare cases, where new parcels had been created that were not yet in the RLR/LPIS data.

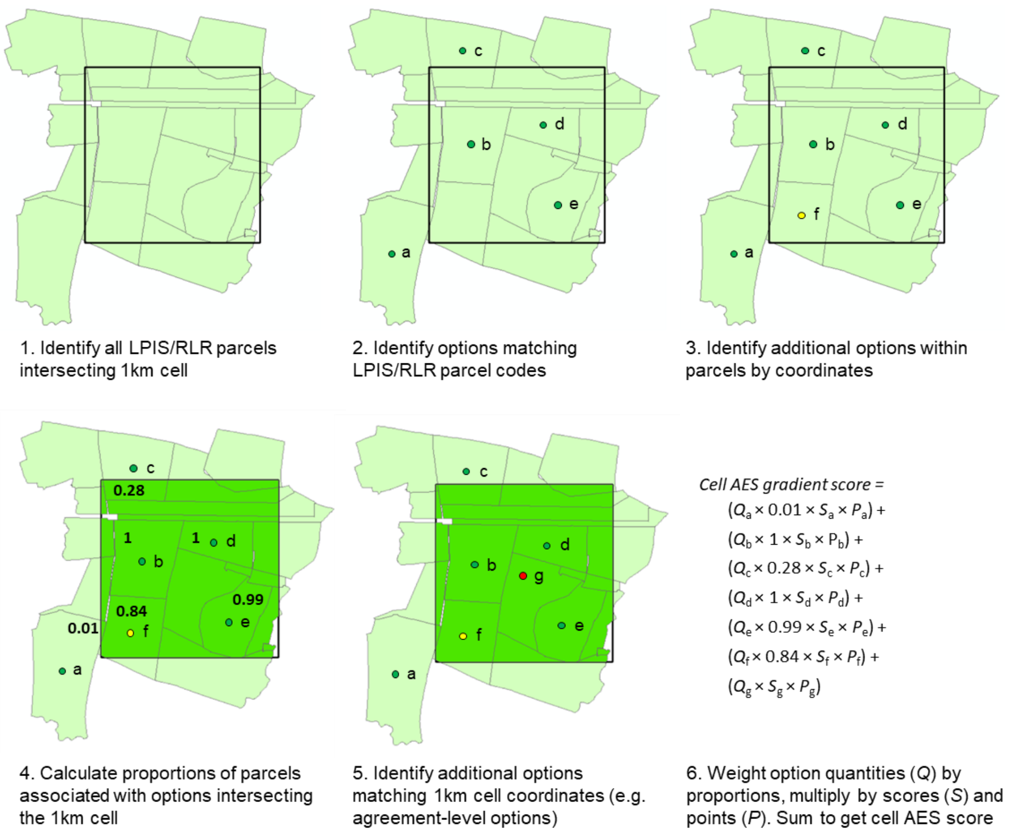

Figure 2.2.1. Schematic of the analytical steps applied to obtain AES gradient scores for an individual 1km grid cell. The quantity of option (Q) was derived from the Natural England option datasets, whilst the associated score where derived from matching option codes to the LandSpAES scoring datasets. Points per unit option quantity (P) were derived from the relevant AES handbooks.

The quantity of each option within the 1km cell was then multiplied by the AES option evidence score derived from LandSpAES, and by the points per unit quantity associated with the option in question, derived from the relevant AES handbooks. The latter step acts as an index to weight options with large areas but low impacts, such as extensive grazing options, and small areas but high impacts, such as arable field margins). Summing this final weighted quantity × evidence score × points over all options associated with the cell gives the final AES gradient score for that 1km cell (Figure 2.2.1, panel 6). The 3km gradient scores were then derived simply by taking the mean score of the surrounding eight cells for every 1km square in England.

We also identified those 1km cells that had > 30% of combined urban, suburban, and freshwater coverage; or > 50% combined broadleaved and coniferous woodland coverage, according to UCKEH Land Cover Map 2015 (LCM2015, Rowland et al. 2017). These cells were excluded as potential candidates for LandSpAES survey cells as pertaining to landscapes other than those associated with AES (Staley et al. 2016) and should thus be excluded from further analyses, including those developed here with CitSci data. In addition, any cells with AES gradient scores >50,000 were excluded from further analyses, as during the LandSpAES project design these high anomalous scores were found to be linked to inaccuracies in the option uptake data (Staley et al. 2016).

All processing of AES uptake and land cover data, and subsequent scoring, was performed in R (version 3.6, R Core Team 2020). The AES gradients calculated for each CitSci scheme dataset were used in the scoping work described in Section 3, and in the analytical work which followed the scoping.

3. Scoping citizen science schemes

3.1 Scoping approach

To identify CitSci schemes that could be useful in determining the potential for LandSpAES results to be seen outside surveyed NCAs we conducted a scoping exercise. Six CitSci schemes were included in the scoping – the Breeding Bird Survey, and five potential insect monitoring schemes (see Table 2.1, and scoping results below).

The scoping process assessed aspects of each CitSci scheme in relation to the specific modelling requirements for this project i.e. comparability with LandSpAES data collection and representativeness of the wider countryside. The results of the scoping reported below should not be interpreted as reflecting the relative merits of the different CitSci schemes for other types of analytical work, or in other contexts.

The same process was used to scope each CitSci scheme against six criteria:

1. *Quantity of data*

The number of CitSci scheme survey squares visited in the same years as the LandSpAES surveys (2017 – 2019), in England, were summarised to show the quantity of data. CitSci schemes with few survey squares visited in these years are less likely to have sufficient data to support modelling of AES gradient effects, or integrated modelling.

Prior to summarising the quantity of data, the CitSci scheme survey sites were filtered to exclude 1 km squares dominated by urban or woodland, using the same criteria that were applied to the LandSpAES survey squares (Staley *et al.* 2016). Squares that had either >50 % woodland or >30 % urban or freshwater were removed from both the scheme squares and the all England set of squares.

2. *Coverage of CitSci data along AES gradients, and correlations between local and landscape AES gradients*

The distributions of AES gradient values for the surveyed sites within the CitSci scheme were plotted for each gradient (local scale, 1 km^2 and landscape scale, 3 × 3 km), along with the distribution of gradient values in England (using a random sample of 1 km squares). To guide interpretation, vertical lines were added at scores of 500 and 5000 (used in the design of LandSpAES to delimit ‘low’, ‘medium’ and ‘high’ AES squares). These categories were used in the survey square selection process for LandSpAES, to ensure contrast between local and landscape gradients. The categories are not used in the analyses of data, for which continuous gradient values are used.

While the plots of AES gradient distribution give some indication of gradient coverage relative to national coverage, the LandSpAES survey was designed to maximise contrast between the local and landscape gradients. Contrast is necessary in order to independently test the effect of local and landscape AES gradients, and interactions between the two gradient scales (see Subtask 2 above). To assess the contrast between local and landscape gradients, the number of squares per gradient category were summarised, and the correlation between the two gradients (using Spearman's rank correlation coefficient).

3. *Evaluate whether AES gradients are confounded with habitat variables*

In the LandSpAES project, the survey squares are grouped within broadly homogenous regions (National Character Areas) to reduce correlations between gradients and habitat variables, but this is not the case with national CitSci scheme survey sites. If the AES gradients are strongly correlated with habitat variables in the national CitSci scheme data, the ability to attribute taxon responses to AES gradients will be reduced. Spearman's rank correlations between six habitat variables and both the local and landscape gradients were calculated for each CitSci scheme. The six habitat variables, calculated for the CitSci 1 km squares using LCM (Morton et al. 2020a,b,c) broad habitat data, were:

i. **Area of arable land**
ii. **Area of grassland**
iii. **Area of semi-natural habitat including acid grassland.** Total area of LCM habitats (with LCM broad habitat code): acid grassland (7), bog (11), broadleaf woodland (1), calcareous grassland (6), coniferous woodland (2), fen marsh swamp (8), freshwater (14), heather (9), heather grassland (10), inland rock (12), neutral grassland (5) and saltmarsh (19)
iv. **Area of semi-natural habitat excluding acid grassland, as acid grassland can be intensively managed and of low value to biodiversity.** Total area of LCM habitats: bog (11), broadleaf woodland (1), calcareous grassland (6), coniferous woodland (2), fen marsh swamp (8), freshwater (14), heather (9), heather grassland (10), inland rock (12), neutral grassland (5) and saltmarsh (19)
v. **Area of semi-natural grassland.** Total area of LCM habitats: neutral grassland (5), calcareous grassland (6), fen marsh swamp (8), heather grassland (10) and heather (9)
vi. **Habitat diversity.** Shannon-Weiner diversity of ten aggregate LCM habitat classes (UKCEH 2020).

4. *Assess distribution in uplands vs lowlands*

CitSci schemes often have better coverage of lowland than upland areas, due to their reliance on volunteers. If a CitSci scheme has little or no upland coverage it can still be used for modelling, but any relationships found with AES gradients may only apply to lowland agricultural landscapes.

5. *Consider whether CitSci data are regionally biased*

There is potential for survey sites within a CitSci scheme to cover only part of England, or to have high AES gradient values in only one region of the country, and all the low values in another region. Data collection in general may also be highly biased regionally. To evaluate this, Spearman's rank correlation coefficients were calculated between the local and landscape AES gradients, and the northing and easting coordinate of each CitSci survey site. This approach will show whether, for example, all the squares with high local AES were in the south for a particular CitSci scheme, though it will not detect more subtle regional patterns.

6. *Summarise differences in survey protocols*

Survey protocols in LandSpAES were designed to be compatible where possible with standard monitoring approaches for each taxon, as are used in existing CitSci schemes. However, due to the variation in survey approaches used across CitSci insect monitoring schemes, and the co-location of taxon monitoring in LandSpAES within 1 km survey squares, there are differences between some CitSci schemes and the monitoring of that taxon within LandSpAES.

Protocol differences were summarised in several categories:

i. **Survey unit.** Some CitSci schemes are designed to representatively survey a 1 km survey square, which is also the survey unit for LandSpAES, while other schemes survey areas that do not exactly match 1 km grid squares. AES gradient values and habitat variables are attributed to 1 km grid squares, so we can be confident that the AES gradient values match the surveyed unit for those CitSci schemes that are designed to survey 1 km squares. For those CitSci schemes where the survey unit does not exactly match a 1 km square, the attribution of AES gradient values may be less accurate.
ii. **Survey season.** Overlap between the survey season for the CitSci scheme and the same taxa surveyed in LandSpAES.
iii. **Survey frequency.** The specified frequency at which CitSci scheme sites are visited each year, compared with the frequency of visits for the same taxa in LandSpAES.
iv. **Survey method.** Are there any differences in the method used on the CitSci scheme and LandSpAES? E.g. if both the CitSci scheme and the LandSpAES project use invertebrate traps, are the same type of traps used?
v. **Survey effort per visit.** Does the survey effort in the CitSci scheme match the survey effort in the LandSpAES project surveys, for each visit. For example, is the same length and width of transect surveyed, or the same number of traps used per survey unit?
vi. **Taxonomic coverage.** Are there any differences in the taxonomic resolution and the breadth of coverage between the CitSci scheme and the LandSpAES data?

3.2 Scoping results for each CitSci scheme

All the results reported below relate to the CitSci scheme sites surveyed in 2017 – 2019 within England, after squares dominated by urban or woodland habitats were removed (see Section 3.1 for details).

3.2.1 Breeding Bird Survey (BBS)

Quantity of data

Table 3.1 Number of BBS squares visited in each year, in England

2017	2018	2019
2302	2346	2302

The BBS is the largest of the CitSci schemes that were scoped for this project, with a substantial number of squares surveyed in each year (Table 3.1).

Coverage of CitSci data along AES gradients, correlation between local and landscape gradients

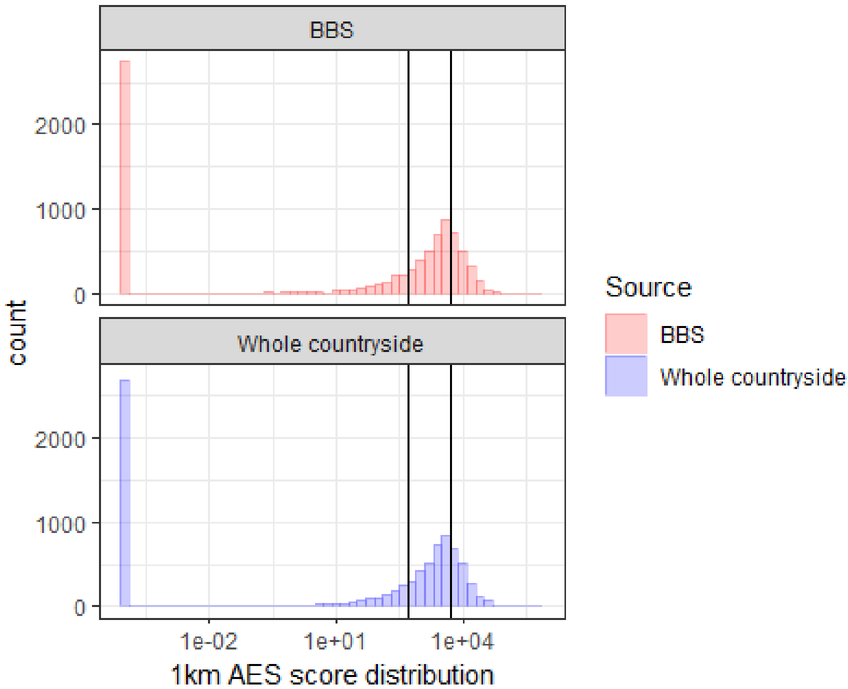

Figure 3.1 Distribution of survey squares along AES local (1 km^2) gradient for BBS (red) squares and nationally in England (blue).

Similar distributions between BBS squares and national distributions suggest that BBS squares are largely representative of the national distribution of AES gradient values (Figures 3.1 and 3.2) and cover a similar range along the gradients.

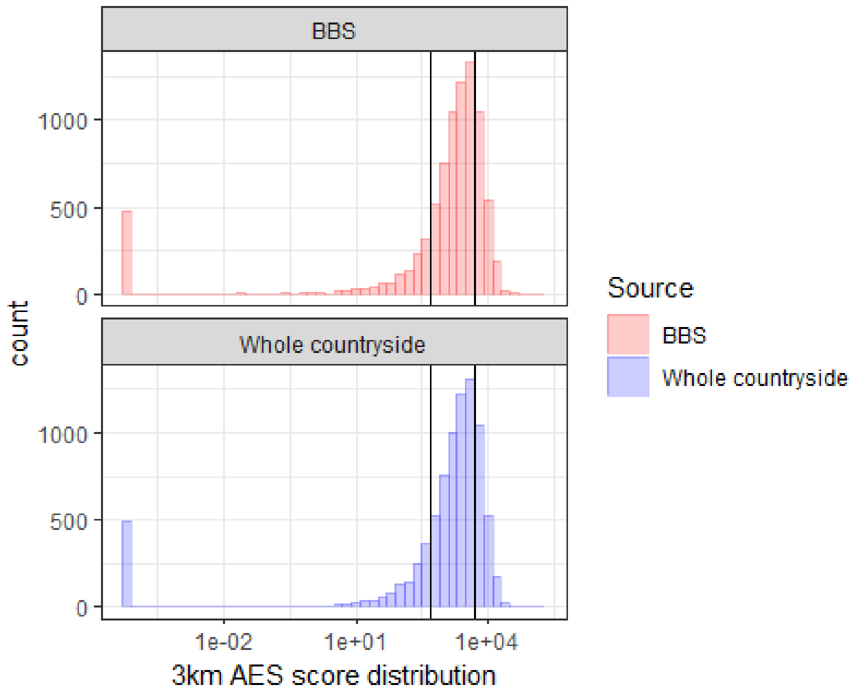

Figure 3.2 Distribution of survey squares along AES landscape (3 × 3 km) gradient for BBS (red) squares and nationally in England (blue).

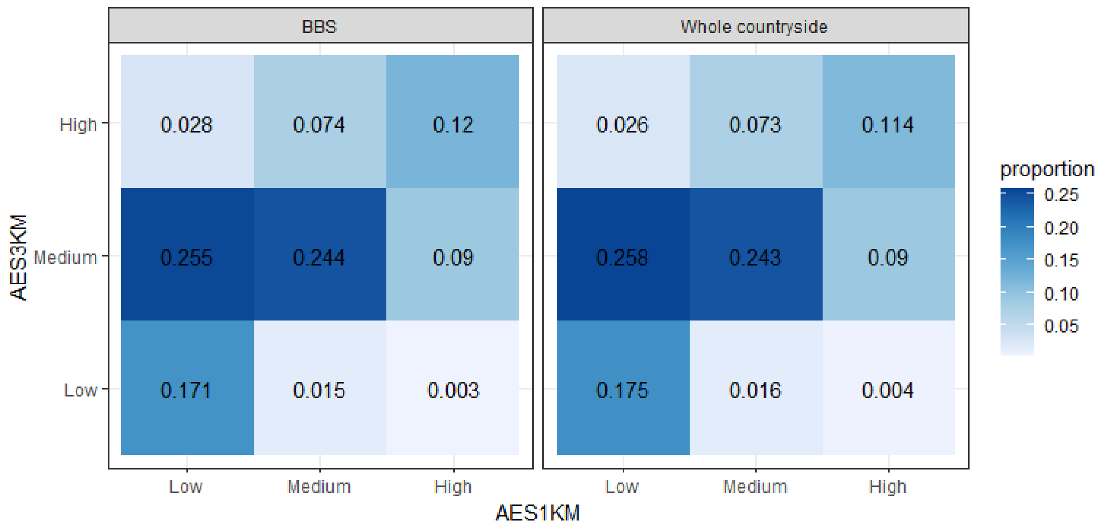

Figure 3.3 Coverage of AES local and landscape gradient categories by BBS squares (left) and nationally in England (right).

The BBS squares cover a good range of AES scores and have representation in all nine AES gradient matrix categories (Figure 3.3). The local and landscape AES gradients for BBS squares are moderately correlated with each other (R = 0.66; Table 3.19), which is expected as CitSci schemes are not designed to maximise contrast between these two gradients.

Are AES gradients confounded with habitat variables?

Table 3.2 Spearman's rank correlations between six habitat variables (see 3.1 for details) and the local (1 km^2) and landscape (3 × 3 km) AES gradients for BBS squares.

Habitat variable	Correlation (R) with AES gradients	
	AES 1km	**AES 3km**
Area of arable	-0.14	-0.13
Area of grassland	0.11	0.12
Area of semi-natural habitat including acid grassland	0.21	0.18
Area of semi-natural habitat excluding acid grassland	0.16	0.13
Area of semi-natural grassland	0.15	0.15
Habitat diversity	-0.02	-0.03

Neither the local or landscape AES gradient values are strongly correlated with any of the habitat variables within BBS squares (Table 3.2). There is indication of a weak correlation (R = 0.21) between the local AES gradient and semi-natural habitat including acid grassland.

Distribution of scheme squares in uplands vs lowlands

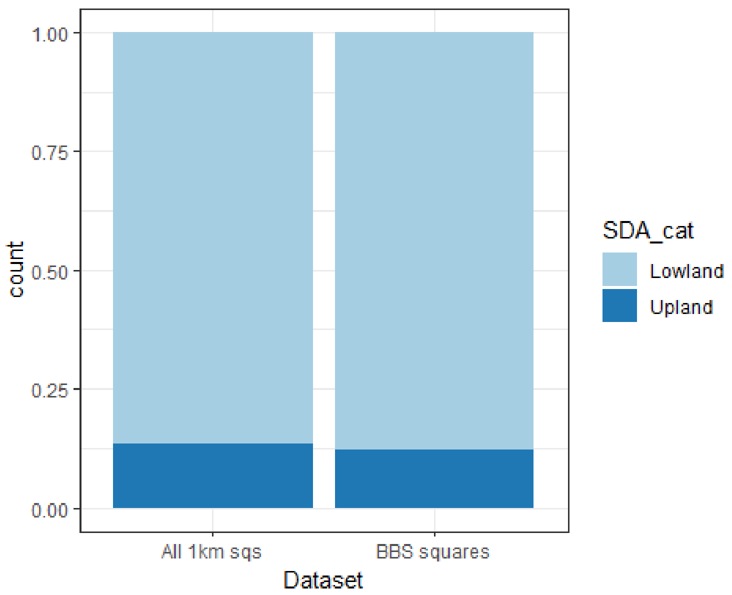

Figure 3.4 Proportion of upland (dark blue) vs lowland (pale blue) squares in BBS scheme (right) and nationally in England (left).

BBS has a slightly lower proportion of upland squares to England as a whole, but any bias towards lowland areas is small (Figure 3.4).

Are the CitSci data regionally biased?

Figure 3.5 Map of BBS survey squares

BBS coverage is fairly good across England (Figure 3.5), and there is no evidence of correlations between AES gradients and either eastings or northings (Table 3.3).

Table 3.3. Spearman's rank correlations between easting and northing coordinates, and the local (1 km^2) and landscape (3 × 3 km) AES gradients for BBS squares.

Coordinate	Correlation with AES gradients	
	AES 1km	**AES 3km**
Easting	-0.05	-0.09
Northing	-0.02	-0.07

Differences in survey protocols between CitSci scheme and the LandSpAES project

The LandSpAES protocol was deliberately designed to be consistent with that of BBS, while also being more intensive. Hence, with the same survey units used at the 1 km square scale, it should be straightforward to integrate the data using a continuous effort variable (transect length) and either accounting for number of survey visits (NB probabilities of detection of most species are not equal between visits at different times during the breeding season) or sub-sampling. The principal differences are as follows:

- BBS uses two visits per year (April to mid-May and mid-May to June), whereas LandSpAES uses four visits (April, early to mid-May, late May to early June and mid-June to mid-July).
- BBS uses two transects, each of 1 km in length. LandSpAES uses a total length of 3 km of transect, divided according to topography and access.

More minor differences are:

- BBS transects are divided into 200 m sections, whereas LandSpAES transects are divided by habitat, such that bird locations can clearly be separated into those discrete habitats.
- LandSpAES birds are recorded as singing or not singing to record territorial activity; BBS birds are recorded by method of detection to facilitate estimation of densities.

• Access via landowner contacts is very high in LandSpAES, but uncontrolled in BBS, so transects in BBS are more likely to be concentrated along rights of way, although all transects in both surveys will be biased towards linear features. Some BBS transects that are nominally within a given 1 km will 'detour' outside of square boundaries due to access limitations; this does not apply to LandSpAES.

3.2.2 Wider Countryside Butterfly Survey (WCBS)

Quantity of data

Table 3.4 Number of WCBS squares visited in each year, in England

2017	2018	2019
510	538	584

The WCBS is one of the two larger insect CitSci schemes that were scoped for this project, with a substantial number of squares surveyed in each year (Table 3.4). The median number of visits per WCBS square per year was two, though some squares received more than two survey visits per year, resulting in 2.19 – 2.30 mean visits per year.

Coverage of CitSci data along AES gradients, correlation between local and landscape gradients

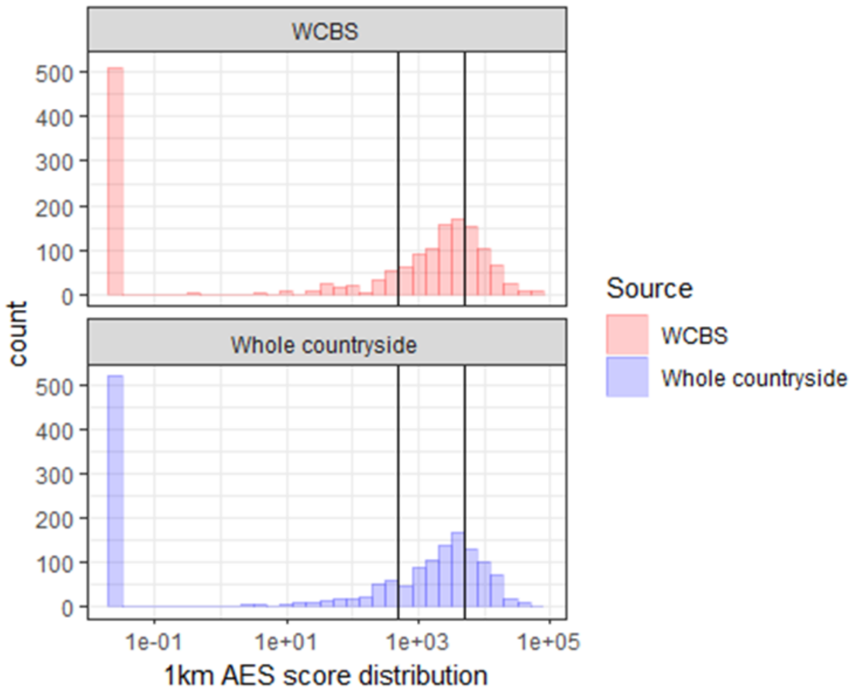

Figure 3.6 Distribution of survey squares along AES local (1 km^2) gradient for WCBS (red) squares and nationally in England (blue).

Similar distributions between WCBS squares and national distributions suggesting WCBS squares are largely representative of the national distribution of AES gradient values (Figures 3.6 and 3.7). The ranges of AES gradients are reasonably comparable.

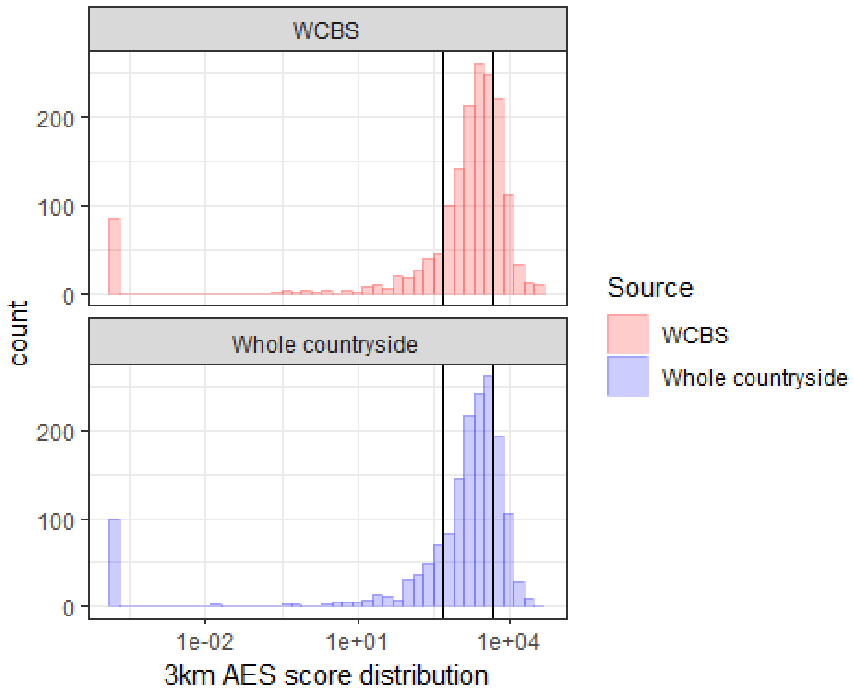

Figure 3.7 Distribution of survey squares along AES landscape (3 × 3 km) gradient for WCBS (red) squares and nationally in England (blue).

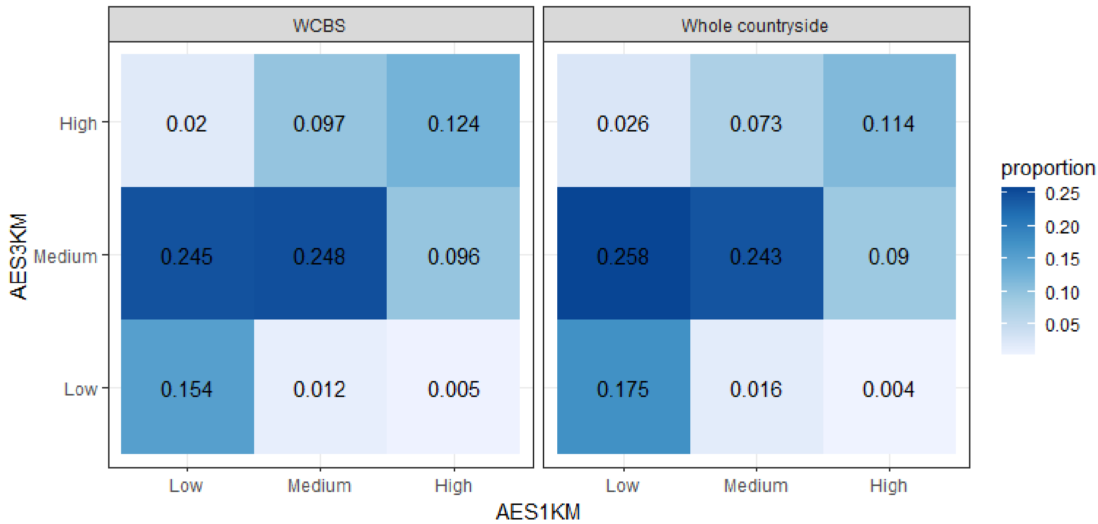

Figure 3.8 Coverage of AES local and landscape gradient categories by WCBS squares (left) and nationally in England (right).

The coverage of the local and landscape gradient categories by WCBS categories is similar to national coverage (Figure 3.8). All categories in the local × landscape gradient matrix have some representation with WCBS squares, although only small numbers of squares exist in the Low_High and High_Low categories (e.g. only eight square visits (0.4%) in High_Low vs 405 (24%) in Medium_Medium).

The local and landscape AES gradients for WCBS squares are moderately correlated with each other (R = 0.67; Table 3.19), similar to the correlation for BBS squares.

Are AES gradients confounded with habitat variables?

Table 3.5 Spearman's rank correlations between six habitat variables (see 3.1 for details) and the local (1 km^2) and landscape (3 × 3 km) AES gradients for WCBS squares.

Habitat variable	Correlation (R) with AES gradients	
	AES 1km	**AES 3km**
Area of arable	-0.13	-0.06
Area of grassland	0.12	0.10
Area of semi-natural habitat including acid grassland	0.19	0.12
Area of semi-natural habitat excluding acid grassland	0.14	0.07
Area of semi-natural grassland	0.18	0.18
Habitat diversity	-0.03	-0.08

Neither the local or landscape AES gradient values are correlated with any of the habitat variables within WCBS squares (Table 3.5).

Distribution of WCBS squares in uplands vs lowlands

Compared to the national coverage of uplands, WCBS only have about half as many upland squares as would be expected if the scheme was representative of the national lowland / upland coverage (Figure 3.9).

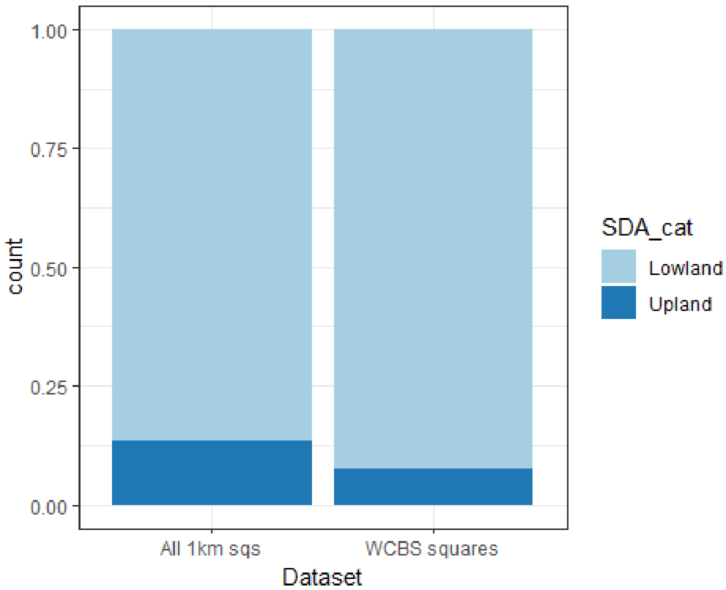

Figure 3.9 Proportion of upland (dark blue) vs lowland (pale blue) squares in WCBS scheme (right) and nationally in England (left).

Are the CitSci data regionally biased?

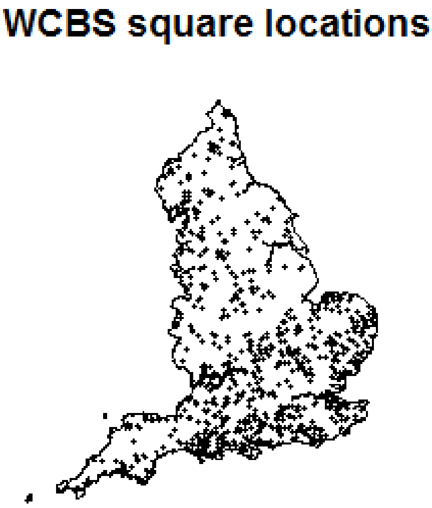

Figure 3.10 Map of WCBS survey squares

There is evidence of a bias towards the south, with sparser coverage of WCBS squares in the Midlands and north (Figure 3.10). WCBS may not be entirely representative of the country, although there are still a fair number of squares in the north. No relationships were found between AES gradients and Eastings or Northings (Table 3.6).

Table 3.6. Spearman's rank correlations between easting and northing coordinates, and the local (1 km^2) and landscape (3 × 3 km) AES gradients for WCBS squares.

Coordinate	Correlation with AES gradients	
	AES 1km	**AES 3km**
Easting	-0.11	-0.11
Northing	-0.12	-0.09

Differences in survey protocols between CitSci scheme and the LandSpAES project

The LandSpAES butterfly survey protocol was deliberately designed to be consistent with that of WCBS, while also being more intensive. The survey unit for both WCBS and the LandSpAES surveys is a 1 km square, so AES gradient scores and habitat variables can be accurately attributed to WCBS survey units.

The survey season and frequency differ between WCBS and LandSpAES butterfly surveys. WCBS squares have a minimum of two monthly visits per year in July & August, with most squares receiving two visits, and some more than two visits, including additional visits earlier in the year. LandSpAES squares receive four monthly visits per year in May – August, so spring and early summer butterfly species are more likely to be consistently detected in LandSpAES surveys.

The survey method is consistent between WCBS and LandSpAES butterfly surveys. Both surveys involve walking a ~2 km fixed transect route, recording butterflies to species within a 5 × 5 × 5 m moving box. The WCBS transect sections are split into equal length sections, whereas in the LandSpAES survey the transect sections are split by habitat type. However, analyses for the current project will use response variables calculated across 1 km survey squares, so the differences in how transects are divided into sections will not affect response variables at the 1 km scale.

The taxonomic coverage is also likely to be comparable, with similar methods used to survey the abundance of difficult species (e.g. netting a proportion of Essex / Small skippers to identify to species).

3.2.3 UK Butterfly Monitoring Scheme

The UKBMS survey season is longer than that of the LandSpAES butterfly surveys (see below). For this scoping work, UKBMS survey data were filtered to only include visits from May – August, to match the LandSpAES butterfly survey season.

Quantity of data

Table 3.7 Number of UKBMS sites visited in each year, in England

2017	2018	2019
879	935	996

The UKBMS is the largest of the insect CitSci schemes that were scoped for this project, with a substantial number of sites surveyed in each year (Table 3.7). On average sites had around 14-15 visits. There is a big range: some sites only had one visit in a year while a small number of sites had many visits (up to 52).

Coverage of CitSci data along AES gradients, correlation between local and landscape gradients

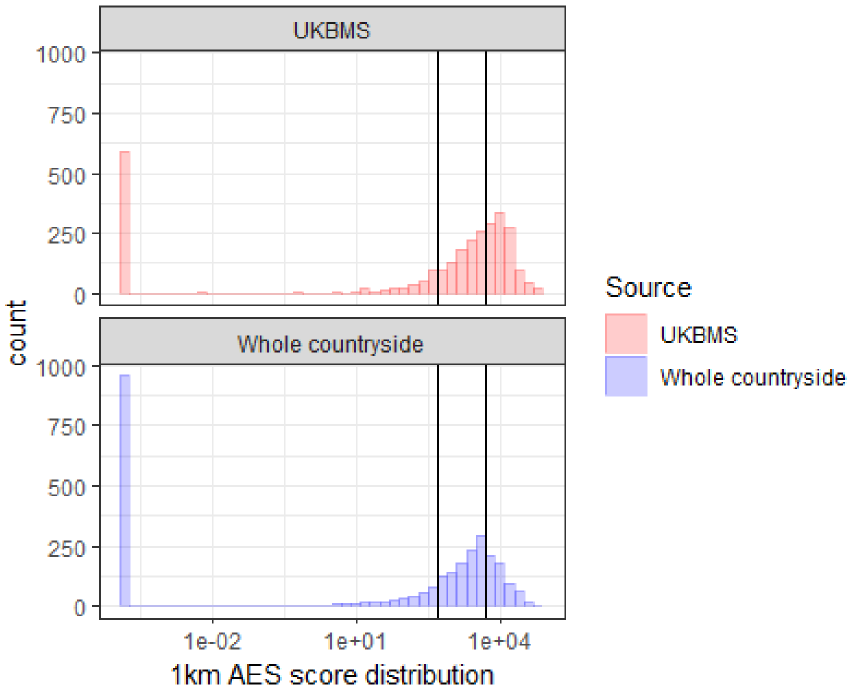

Figure 3.11 Distribution of survey sites along AES local (1 km^2) gradient for UKBMS (red) squares and nationally in England (blue).

UKBMS sites are slightly skewed to higher local AES (Figure 3.11), perhaps due to UKBMS sites being placed in higher quality habitat areas. UKBMS transect routes are determined by the volunteer who walks them, or the landowner / manager, and are often planned to provide information about the effects of local habitat management on butterflies.

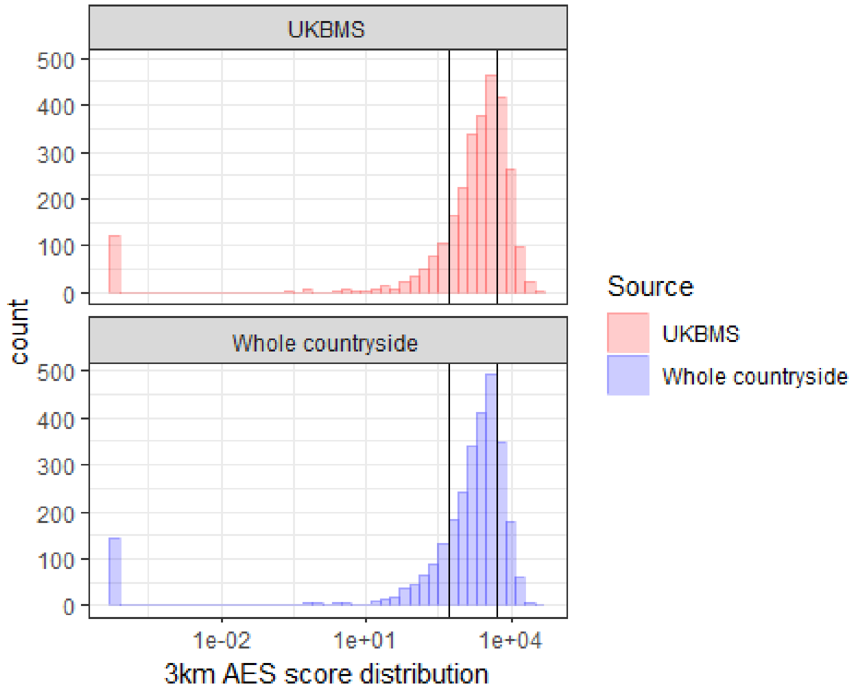

Figure 3.12 Distribution of survey sites along AES landscape (3 × 3 km) gradient for UKBMS (red) squares and nationally in England (blue).

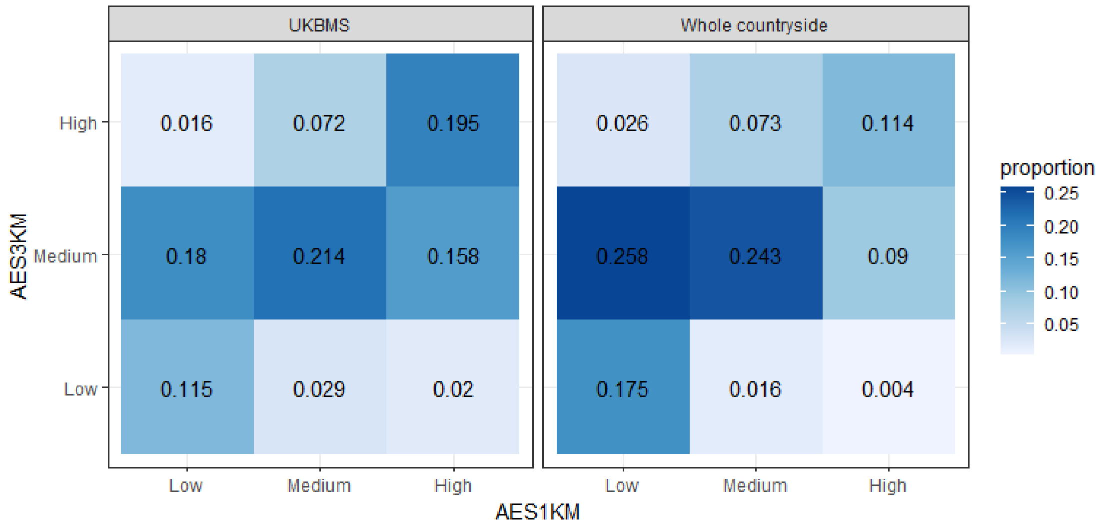

Figure 3.13 Coverage of AES local and landscape gradient categories by UKBMS sites (left) and nationally in England (right).

Overall UKBMS squares seem to cover all categories, and have a slightly higher proportion of High_Low squares than the national average (Figure 3.13). There is a higher proportion of squares in the high local categories than nationally.

The local and landscape AES gradients for UKBMS squares are moderately correlated with each other (R = 0.62; Table 3.19), similar to the correlations between these gradient scales for the WCBS and BBS scheme squares.

Are AES gradients confounded with habitat variables?

Table 3.8 Spearman's rank correlations between six habitat variables (see 3.1 for details) and the local (1 km^2) and landscape (3 × 3 km) AES gradients for UKBMS squares.

Habitat variable	**Correlation (R) with AES gradients**	
	AES 1km	**AES 3km**
Area of arable	-0.14	-0.11
Area of grassland	0.17	-0.13
Area of semi-natural habitat including acid grassland	0.15	0.14
Area of semi-natural habitat excluding acid grassland	0.13	0.12
Area of semi-natural grassland	0.20	0.24
Habitat diversity	-0.06	-0.14

There is not much evidence of relationships between AES gradients and habitat variables at UKBMS sites (Table 3.8). There may be a slight positive correlation with semi-natural grassland area but it is quite weak.

Distribution of UKBMS sites in uplands vs lowlands

UKBMS squares have a lower proportion of upland sites than the national average, suggesting the uplands are poorly represented in the UKBMS sample (Figure 3.14).

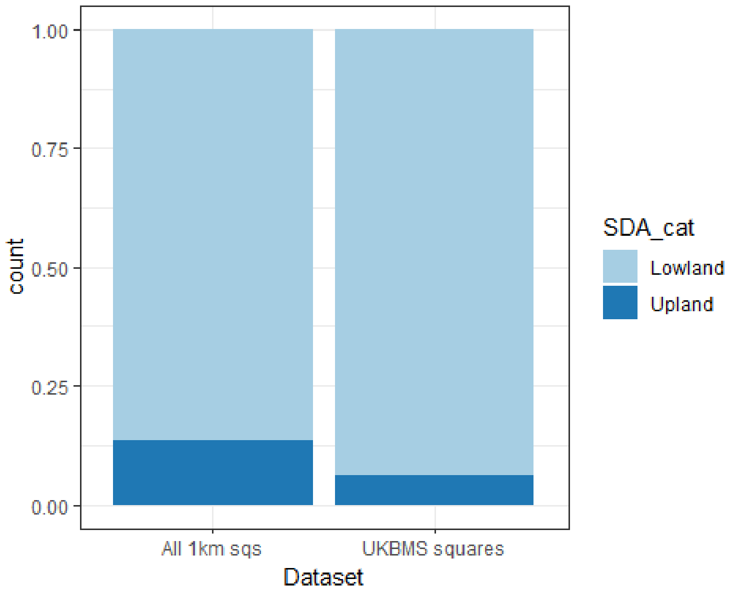

Figure 3.14 Proportion of upland (dark blue) vs lowland (pale blue) sites in UKBMS scheme (right) and nationally in England (left).

Are the CitSci data regionally biased?

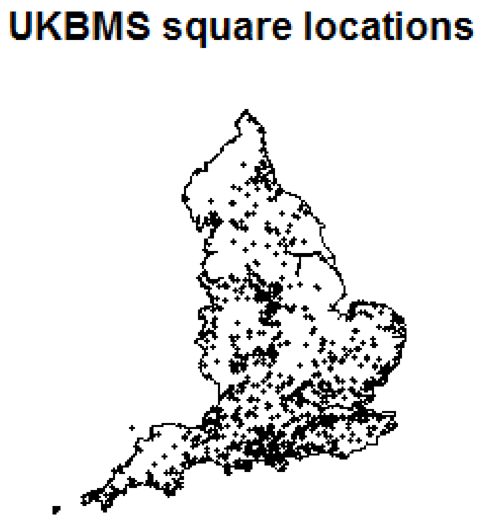

Figure 3.15 Map of UKBMS survey sites

There is some evidence of a bias towards the south in UKBMS site locations and away from the north of England. There are large spatial gaps in Cumbria, Northumbria, Lincolnshire and other parts of the Midlands and North (Figure 3.15). There is no indication of correlations between either the local or the landscape AES gradients and Easting or Northing coordinates (Table 3.9).

Table 3.9. Spearman's rank correlations between easting and northing coordinates, and the local (1 km^2) and landscape (3 × 3 km) AES gradients for UKBMS squares.

Coordinate	Correlation with AES gradients	
	AES 1km	**AES 3km**
Easting	-0.09	-0.11
Northing	-0.18	-0.16

Differences in survey protocols between CitSci scheme and the LandSpAES project

UKBMS transect routes may survey outside a 1 km grid square. UKBMS site grid references are attributed to the centre of the UKBMS transect route, and within the timescale of this project an accurate spatial dataset for all sites and the different sections was not available to determine how much of the transect route is within each 1km square for UKBMS.

The survey method is broadly consistent between UKBMS and LandSpAES butterfly surveys. Both surveys involve walking a fixed transect route, recording butterflies to species within a 5 × 5 × 5 m moving box. The taxonomic coverage is also likely to be comparable, with similar methods used to identify difficult species (e.g. netting a proportion of Essex / Small skippers to identify to species). UKBMS transect lengths may vary greatly between sites compared to the LandSpAES butterfly transect lengths, which are all around 2 km in length. Transect length can be included in the analyses.

The survey season and frequency differ between UKBMS and LandSpAES butterfly surveys. UKBMS surveys cover a wider season (April – September) than LandSpAES butterfly surveys (May – August). For the purpose of this scoping, the UKBMS data were filtered to visits between May – August. UKBMS sites are visited more frequently, with many visited weekly, whereas the LandSpAES butterfly surveys are carried out monthly.

While there are more differences between the UKBMS survey and LandSpAES butterfly survey structures (compared to WCBS and LandSpAES), the UKBMS data does include spring / early summer surveys in May and June, which WCBS does not do consistently as earlier visits are optional. Therefore, it was decided to use both butterfly CitSci schemes in the analytical work, but keep them separate for modelling given the protocol differences.

3.2.4 BeeWalk

The BeeWalk CitSci scheme survey season is longer than that of the LandSpAES bumblebee surveys (see below). For this scoping work, BeeWalk survey data were filtered to only include visits from May – August, to match the LandSpAES bumblebee survey season.

Quantity of data

Table 3.10 Number of BeeWalk sites visited in each year, in England

2017	2018	2019
160	210	241

There are fewer BeeWalk sites visited than for the two butterfly CitSci schemes (Table 3.10), perhaps reflecting the BeeWalk CitSci scheme having been set up more recently. However, there are still a substantial number of sites visited in 2017 – 2019. On average there were four visits to BeeWalk sites during May – August, but a few sites had more frequent visits.

Coverage of CitSci data along AES gradients, correlation between local and landscape gradients

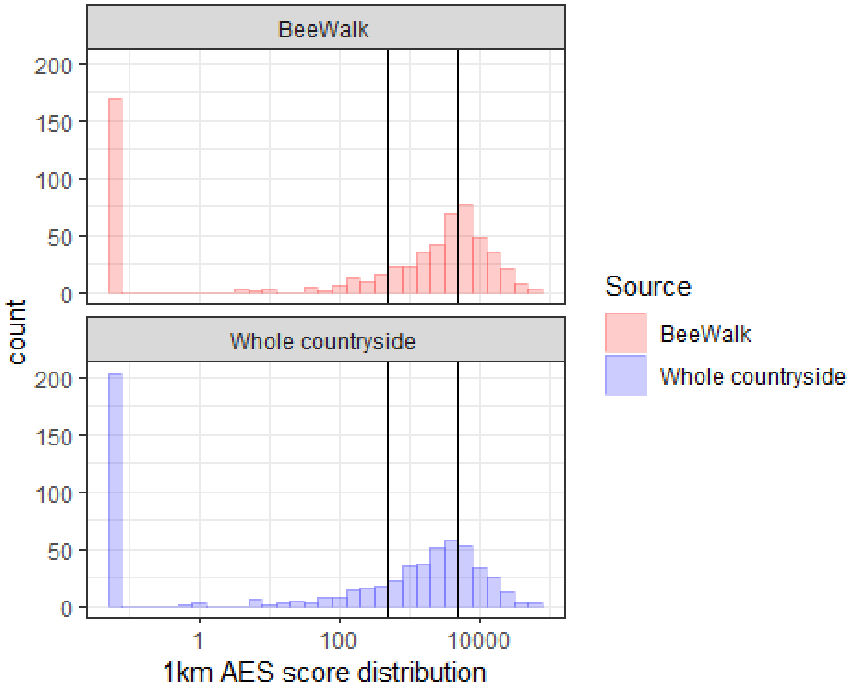

Figure 3.16 Distribution of survey sites along AES local (1 km^2) gradient for BeeWalk (red) squares and nationally in England (blue).

BeeWalk sites cover the distributions of AES scores quite well (Figures 3.16 and 3.17), though with a slightly smaller range of AES scores as might be expected given the number of BeeWalk sites.

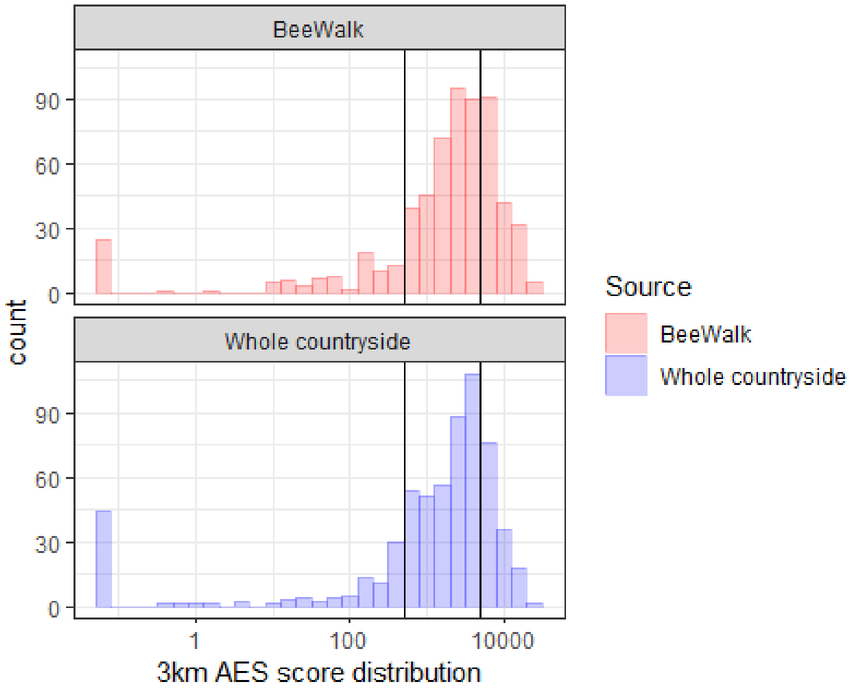

Figure 3.17 Distribution of survey sites along AES landscape (3 × 3 km) gradient for BeeWalk (red) squares and nationally in England (blue).

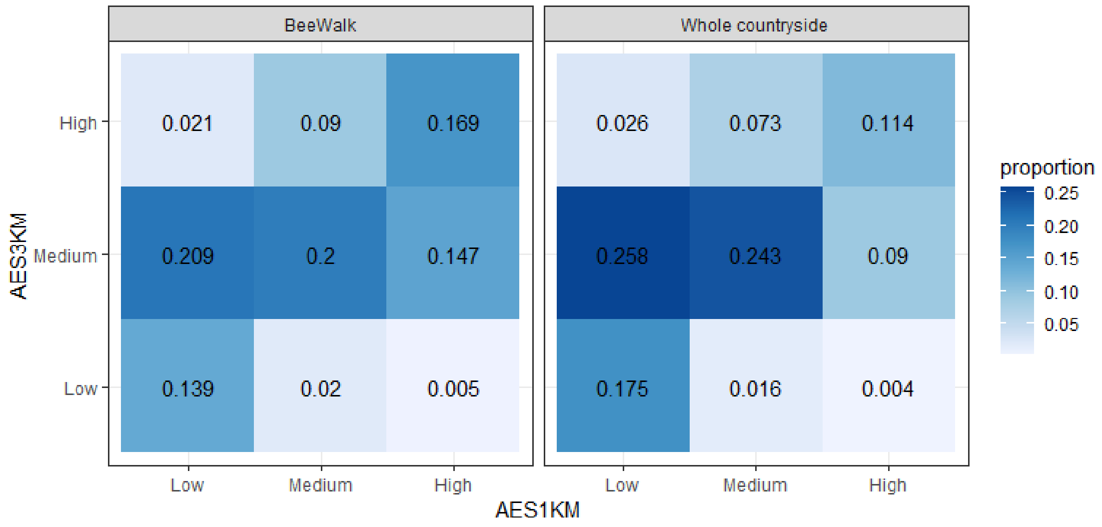

Figure 3.18 Coverage of AES local and landscape gradient categories by UKBMS sites (left) and nationally in England (right).

BeeWalk data covers all the AES categories, though there is slight evidence of oversampling in high AES, similar to UKBMS (Figure 3.18).

The local and landscape AES gradients for BeeWalk sites are moderately correlated with each other (R = 0.63; Table 3.19), similar to the correlation for the butterfly and the BBS CitSci schemes.

Are AES gradients are confounded with habitat variables?

Table 3.11 Spearman's rank correlations between six habitat variables (see 3.1 for details) and the local (1 km^2) and landscape (3 × 3 km) AES gradients for BeeWalk squares.

Habitat variable	**Correlation (R) with AES gradients**	
	AES 1km	**AES 3km**
Area of arable	-0.29	-0.18
Area of grassland	0.26	0.27
Area of semi-natural habitat including acid grassland	0.27	0.23
Area of semi-natural habitat excluding acid grassland	0.21	0.19
Area of semi-natural grassland	0.25	0.27
Habitat diversity	-0.06	-0.12

There are a few weak correlations between AES scores and habitat variables at BeeWalk sites (Table 3.11), for example between the AES gradients and each of grassland, area of semi-natural habitat (including acid grassland), and area of semi-natural grassland. There is also a weak negative correlation between the local AES gradient and the cover of arable land. No moderate or strong correlations were found between AES gradients and habitat variables at BeeWalk sites.

Distribution of BeeWalk sites in uplands vs lowlands

BeeWalk sites include a fairly good representation of upland squares, these are only slightly under-sampled (Figure 3.19).

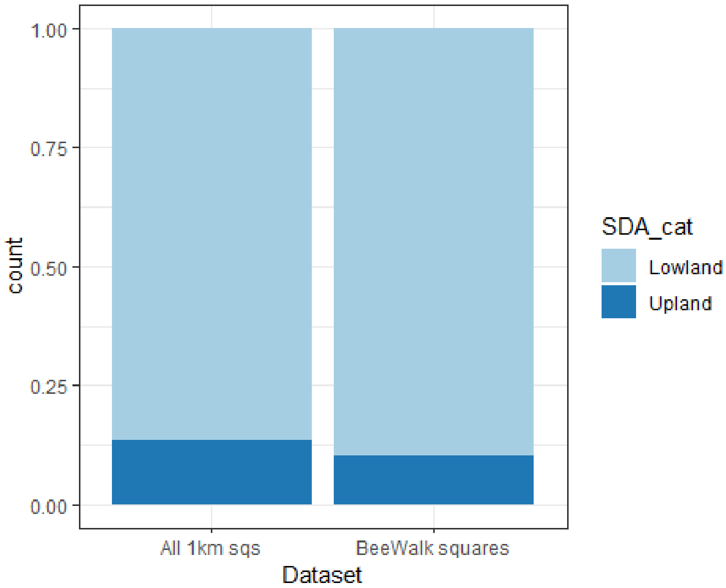

Figure 3.19 Proportion of upland (dark blue) vs lowland (pale blue) sites in BeeWalk scheme (right) and nationally in England (left).

Are the CitSci data regionally biased?

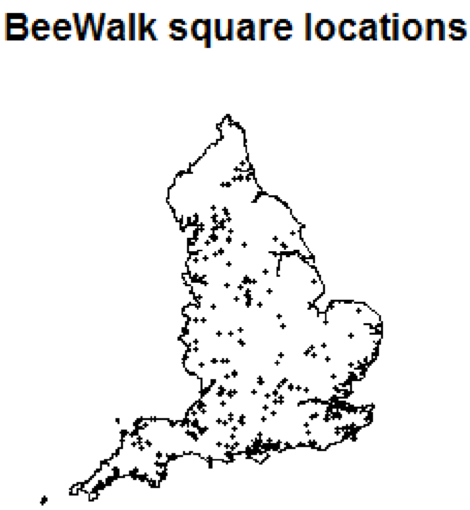

Figure 3.20 Map of BeeWalk survey sites

Overall, there is a reasonable spread of BeeWalk squares (Figure 3.20) although there are regions with no or few squares across the country, which is inevitable given the smaller number of BeeWalk sites, compared with the butterfly and BBS CitSci schemes.

Table 3.12. Spearman's rank correlations between easting and northing coordinates, and the local (1 km^2) and landscape (3 × 3 km) AES gradients for BeeWalk squares.

Coordinate	**Correlation with AES gradients**	
	AES 1km	**AES 3km**
Easting	-0.24	-0.19
Northing	0.05	0.01

No strong correlations were found between the AES gradients and Eastings or Northings at BeeWalk sites (Table 3.12), although there is some indication of a weak correlation between the Easting and local AES gradient.

Differences in survey protocols between CitSci scheme and the LandSpAES project

Similar to UKBMS, BeeWalk transect routes may survey outside a 1 km grid square. BeeWalk site grid references are attributed to the centre of the BeeWalk transect route, and currently data are not available to determine how much of the transect route is within that square for all BeeWalk sites.

The survey method is broadly consistent between BeeWalk and LandSpAES bumblebee surveys. Both surveys involve walking a fixed transect route, recording bumblebees to species. On BeeWalk recording takes place within a 4 × 4 × 4 m moving box, whereas on LandSpAES bumblebee surveys recording is over a larger area (5 × 5 × 5 m moving box, for consistency with the LandSpAES butterfly surveys). BeeWalk transects are typically between 1 and 2 km long, and the length varies more between sites than LandSpAES bumblebee transect lengths, which are around 2 km long. Transect length can be included in the analyses. The survey season and frequency differ between BeeWalk and LandSpAES bumblebee surveys. BeeWalk surveys cover a wider season (March – October) than LandSpAES bumblebee surveys (May – August). For the purpose of this scoping, the BeeWalk data were filtered to visits between May – August. Most BeeWalk sites are visited monthly, though some are visited more frequently, whereas the LandSpAES butterfly surveys are carried out monthly.

3.2.5 Pollinator Monitoring Scheme (PoMS)

Quantity of data

Table 3.13 Number of PoMS squares visited in each year, in England

2017	**2018**	**2019**
33	30	30

There are substantially fewer squares visited for PoMS than for butterfly or bumblebee schemes (Table 3.13), although this scheme only started in 2017. In addition, in 2017 the maximum number of survey visits for a PoMS square was two, as the scheme did not start at the beginning of the 2017 survey season. Only 11 PoMS squares had all four scheduled visits in 2018, and only 13 in 2019 (Table 3.14).

Table 3.14 Number of visits to PoMS squares in each year

	Number of visits			
	1	**2**	**3**	**4**
2017	11	22	0	0
2018	7	4	8	11
2019	1	7	9	13

Coverage of CitSci data along AES gradients, correlation between local and landscape gradients

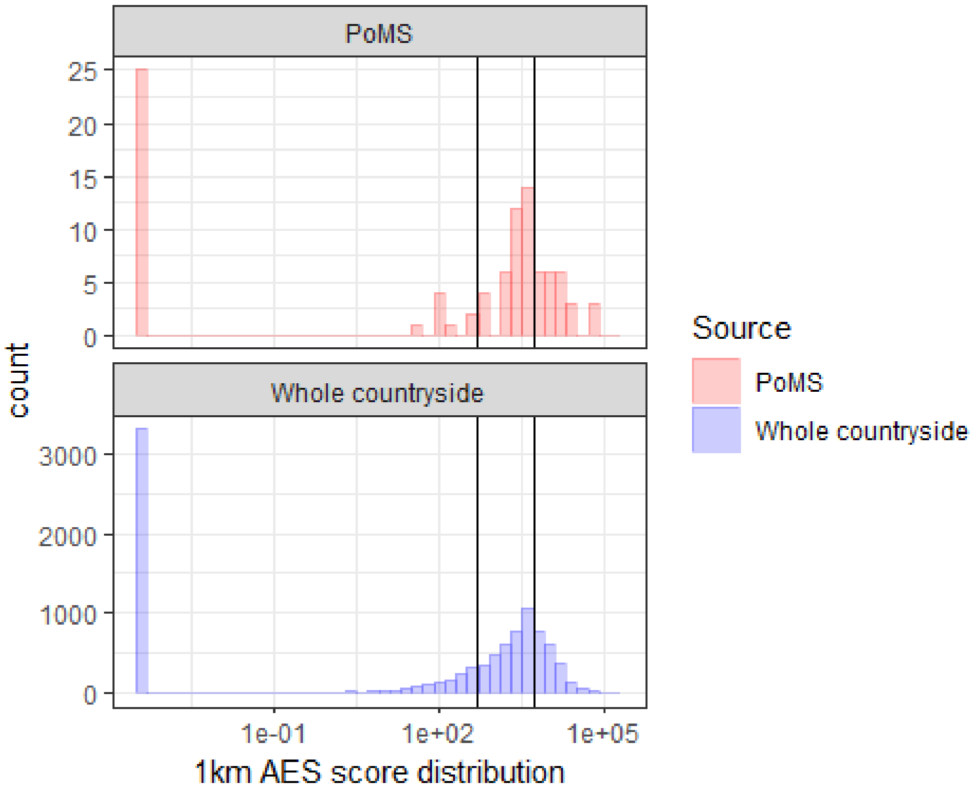

Figure 3.21 Distribution of survey sites along AES local (1 km^2) gradient for PoMS (red) squares and nationally in England (blue).

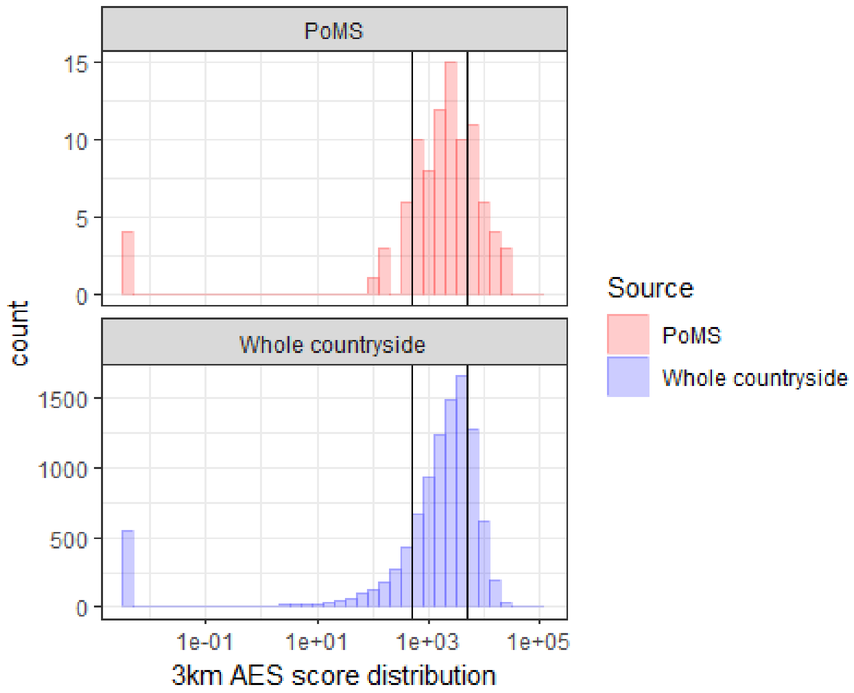

Figure 3.22 Distribution of survey sites along AES landscape (3 × 3 km) gradient for PoMS (red) squares and nationally in England (blue).

PoMS squares appear to have fewer low landscape AES gradient scores than the national distributions (Figures 3.21 and 3.22).

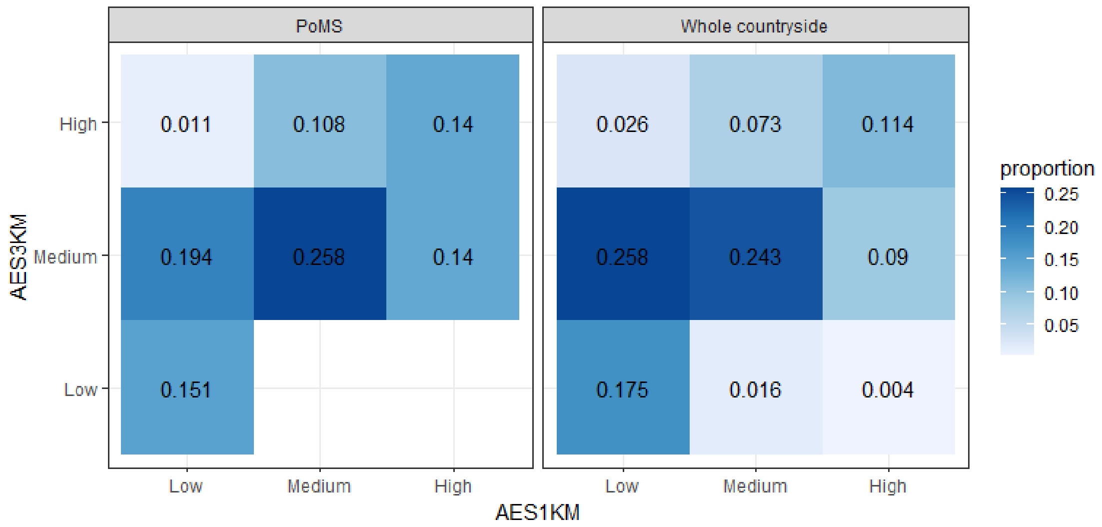

Figure 3.23 Coverage of AES local and landscape gradient categories by PoMS squares (left) and nationally in England (right).

Overall PoMS squares are more likely to be in high and medium AES categories (Figure 3.23). There are no squares in the High_Low (high local, low landscape) or Medium_Low categories, which might be related to the overall low proportions of these across England and the small number of squares sampled here - we would only expect ~1 square to be sampled in each of these categories if it was representative of the whole of England. We can conclude that the PoMS squares cover a range of AES scores but have poor representation in lower AES score landscapes.

The local and landscape AES gradients for BeeWalk sites are moderately correlated with each other (R = 0.62; Table 3.19), similar to the correlations found for other CitSci schemes.

Are AES gradients confounded with habitat variables?

Table 3.15 Spearman's rank correlations between six habitat variables (see 3.1 for details) and the local (1 km^2) and landscape (3 × 3 km) AES gradients for PoMS squares.

Habitat variable	Correlation (R) with AES gradients	
	AES 1km	**AES 3km**
Area of arable	-0.47	-0.42
Area of grassland	0.43	0.35
Area of semi-natural habitat including acid grassland	0.36	0.46
Area of semi-natural habitat excluding acid grassland	0.39	0.48
Area of semi-natural grassland	0.24	0.61
Habitat diversity	0.09	-0.03

The relationships between AES gradient values and habitat variables appear stronger for PoMS squares (Figure 3.32) than for the other CitSci schemes. The AES gradients have weak positive correlations with grassland and semi-natural habitat, and weak negative correlations with arable habitats at PoMS sites. However, there are fewer sites in the PoMS scheme than the other schemes.

Distribution of PoMS sites in uplands vs lowlands

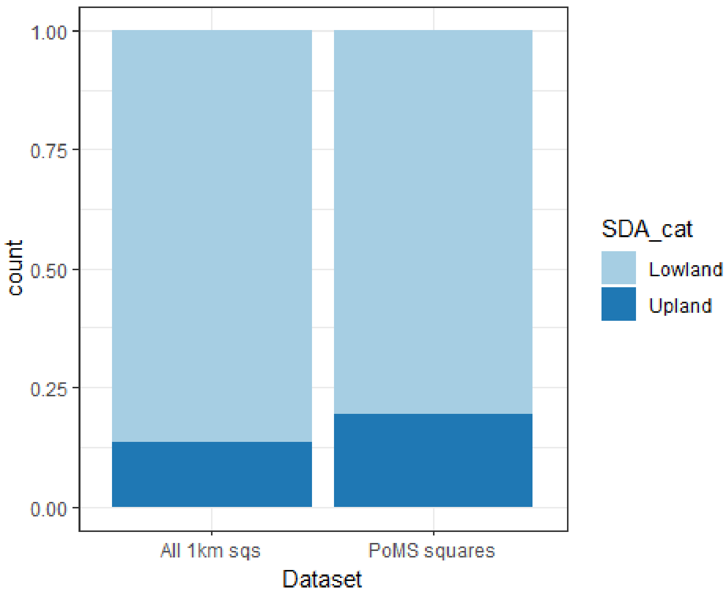

Figure 3.24 Proportion of upland (dark blue) vs lowland (pale blue) squares in PoMS scheme (right) and nationally in England (left).

PoMS squares slightly over represent upland habitats compared to the distribution of all England squares (Figure 3.24).

Are the CitSci data regionally biased?

Figure 3.25 Map of PoMS survey sites

Sites appear to cover most of England and show limited bias, however overall coverage is poor due to low number of sites (Figure 3.25).

Table 3.16. Spearman's rank correlations between easting and northing coordinates, and the local (1 km^2) and landscape (3 × 3 km) AES gradients for PoMS squares.

Coordinate	Correlation with AES gradients	
	AES 1km	**AES 3km**
Easting	-0.14	-0.34
Northing	-0.21	-0.11

No moderate or strong correlations were found between AES gradients and Eastings or Northings at PoMS sites (Table 3.16).

Differences in survey protocols between CitSci scheme and the LandSpAES project

The LandSpAES pan trap surveys for bees and hoverflies were designed to be compatible with the PoMS CitSci scheme, and both started in 2017. Both LandSpAES and PoMS cover a 1 km square survey unit, and have the same survey season (May – August), and frequency of visits (one each month). As PoMS is a volunteer scheme, not all squares receive four visits each year (see above).

The survey method is broadly consistent between PoMS and LandSpAES pan trap surveys, both of which involve setting pan trap stations for six hours. The pan trap stations are made to the same design. The sampling effort is slightly greater on LandSpAES, which uses six pan traps per 1 km square, compared with five pan traps for PoMS. In PoMS three pan traps are placed along a diagonal line at fixed equally spaced intervals, with two pan traps offset from the diagonal line. The LandSpAES pan trap positions are associated with transect sections and spread across the 1 km square representatively, but may also be affected by the access agreed for surveys. On both surveys there is occasional disturbance of a pan trap station, so fewer traps may be sampled for a given visit than the six or five that are set. The number of working traps per visit is included in analyses.

Both PoMS and LandSpAES use professional taxonomists to identify the bees and hoverflies to species from the samples collected, so the level of taxonomic resolution is likely to be highly comparable. The majority of bees and hoverflies are identified to species for both surveys.

3.2.6 Rothamsted insect survey – moth light traps (RIS moth light traps)

Quantity of data

Thirty-three RIS moth light trap sites were operational in 2017 – 2019. Sites are trapped every night except where there is a fault with the trap and therefore can be visited up to 365 times a year.

Coverage of CitSci data along AES gradients, correlation between local and landscape gradients

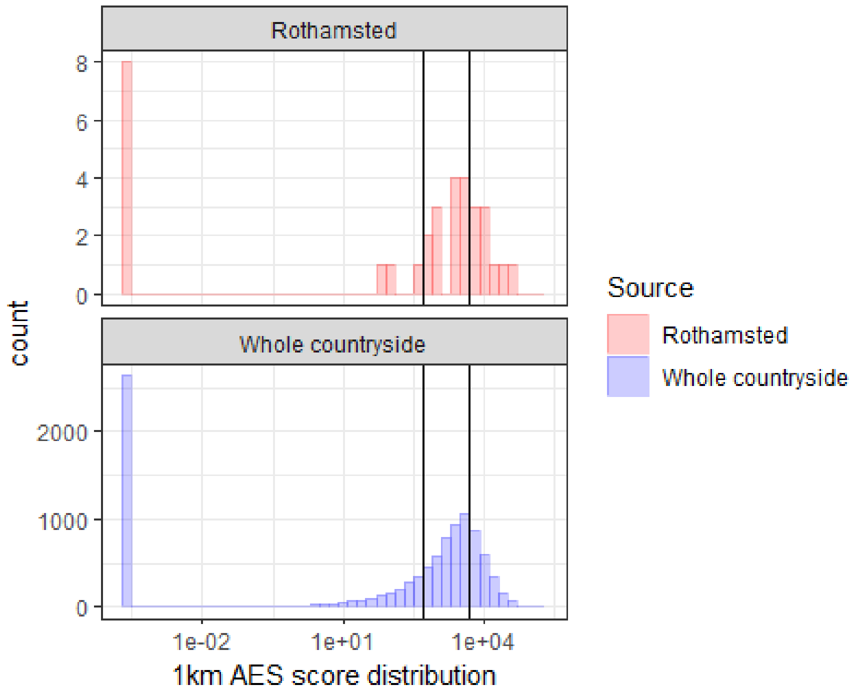

Figure 3.26 Distribution of survey sites along AES local (1 km^2) gradient for RIS moth light traps (Rothamsted, red) sites and nationally in England (blue).

There are fewer RIS light trap sites at the low end of the AES gradients (Figures 3.26 and 3.27), however this may be related to the overall low number of sites.

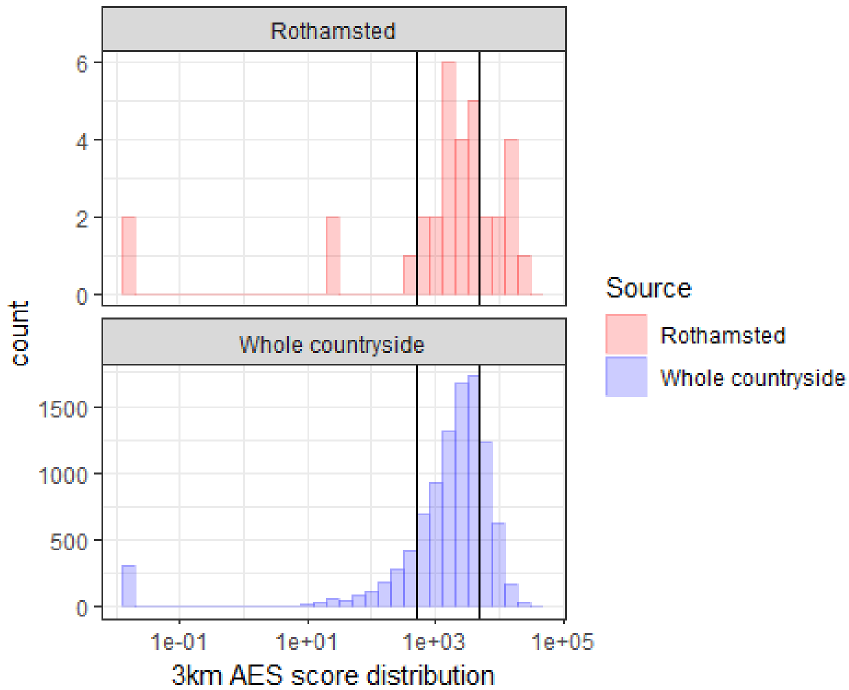

Figure 3.27 Distribution of survey sites along AES landscape (3 × 3 km) gradient for RIS moth light traps (Rothamsted, red) squares and nationally in England (blue).

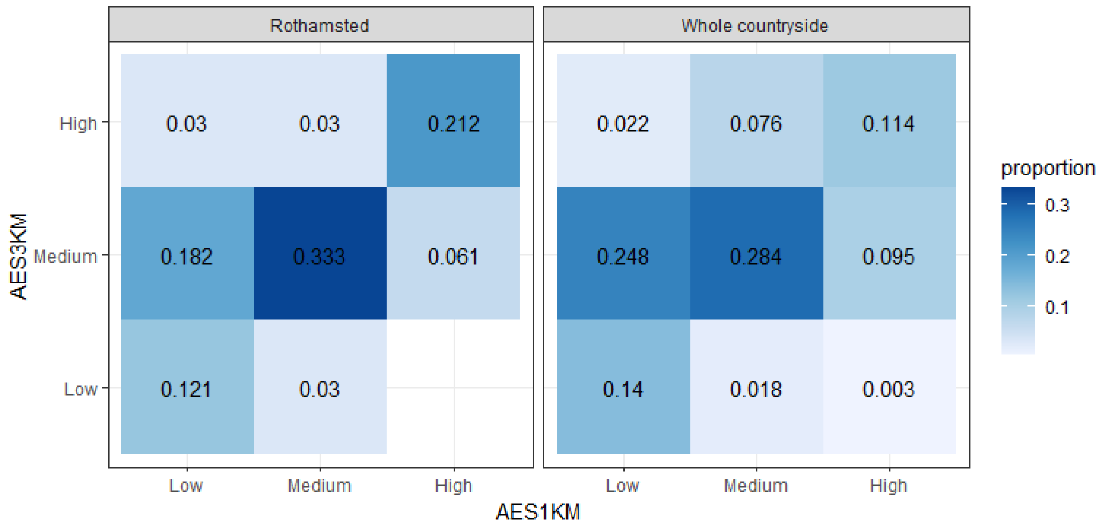

Figure 3.28 Coverage of AES local and landscape gradient categories by RIS moth light trap sites (left) and nationally in England (right).

Overall RIS light trap sites are more likely to be in medium and high AES categories, though there are no sites with high local AES and low landscape AES gradients (Figure 3.28). The local and landscape AES gradients for RIS light trap sites are strongly correlated with each other (R = 0.74; Table 3.19). This correlation between AES gradients is stronger than that found for any of the other CitSci schemes. The strength of correlation means it is unlikely that effects of local and landscape AES gradients could be separated in analyses of RIS moth data.

Are AES gradients confounded with habitat variables?

Table 3.17 Spearman's rank correlations between six habitat variables (see 3.1 for details) and the local (1 km^2) and landscape (3 × 3 km) AES gradients for RIS moth light trap sites.

Habitat variable	Correlation (R) with AES gradients	
	AES 1km	AES 3km
Area of arable	-0.36	-0.24
Area of grassland	0.43	0.34
Area of semi-natural habitat including acid grassland	0.38	0.42
Area of semi-natural habitat excluding acid grassland	0.30	0.39
Area of semi-natural grassland	0.58	0.72
Habitat diversity	-0.20	-0.16

There are a few moderate correlations between AES scores and habitat variables at RIS light trap sites (Table 3.17), for example between the AES gradients and each of grassland, area of semi-natural habitat (including acid grassland) and area of semi-natural grassland. The only strong correlation is between the AES landscapes (3 km) gradient and the area of semi-natural grassland.

Distribution of RIS light trap sites in uplands vs lowlands

RIS light trap sites have reasonably good coverage of upland areas, and these are only slightly under-represented (Figure 3.29).

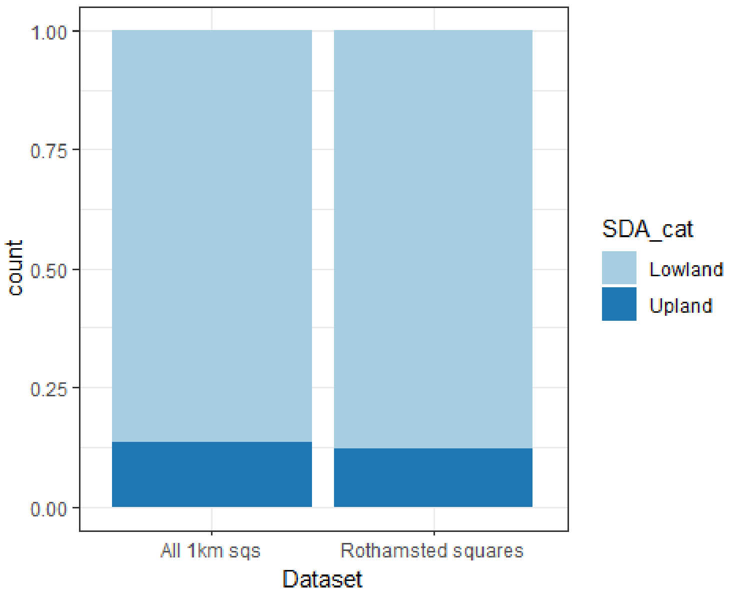

Figure 3.29 Proportion of upland (dark blue) vs lowland (pale blue) sites in RIS moth light trap scheme (right) and nationally in England (left).

Are the CitSci data regionally biased?

Figure 3.30 Map of RIS moth light trap sites

Table 3.18. Spearman's rank correlations between easting and northing coordinates, and the local (1 km^2) and landscape (3 × 3 km) AES gradients for RIS moth light trap sites.

Coordinate	Correlation with AES gradients	
	AES 1km	**AES 3km**
Easting	-0.36	-0.19
Northing	0.4	0.27

Overall, there are more RIS light trap sites in the south around London (Figure 3.30). There are moderate correlations between the local AES gradient and the Easting and Northings (Table 3.18). The highest AES gradient value for RIS light traps is found to the north-west.

Differences in survey protocols between CitSci scheme and the LandSpAES project

In LandSpAES six portable heath-style light traps, with a 6W UV fluorescent tube (actinic) as a light source, are used to representatively cover a 1 km survey (subject to access permissions). A RIS moth light trap site consists of a single high standing standardised trap designed by Rothamsted, using a 200W clear incandescent bulb. Similar to UKBMS and BeeWalk, the RIS moth survey unit is therefore not a 1 km grid square. The survey unit will be the area of attraction around the light trap, which is likely to vary with the level of background light pollution and surrounding habitat type. An additional constraint is that RIS light traps require a mains electricity connection, so are more likely to be near buildings whereas the portable actinic light traps used in LandSPAES are powered by portable rechargeable lead acid batteries.

The survey season and frequency differ between the RIS moth survey and LandSpAES moth surveys. RIS moth light trap surveys cover the entire year: traps are set on automatic timers to catch moths every night and checked daily where possible. LandSpAES moth surveys consist of two surveys a year, one in May/June and one in July/August, each consisting of six traps.

In both the RIS and LandSpAES moth surveys destructive sampling is used: the captured moths are stored and identified later. The level of resolution is likely to be similar for macro-moths across the two surveys, and the majority of identification is at species level. However, the RIS moth survey currently only consistently records macro-moths (with the exception of a small number of common migrant or pest micro-moth species), whereas the LandSpAES moth survey identifies all moths, including those species which need to be dissected for species-level identification.

3.3 Conclusions from scoping exercise

Six potential CitSci monitoring schemes were scoped in terms of their suitability for the modelling work in this project as detailed above: the BBS and five insect monitoring schemes. The CitSci datasets considered here are long-term monitoring schemes designed to look at change in populations over time, and were not designed to test the effects of AES gradients. The scoping process only relates to suitability of each CitSci monitoring scheme for use in the planned modelling work on this project, and should not be interpreted as an assessment of the suitability of each scheme for other types of analyses or in other contexts.

Table 3.19 Correlations between local ($1km^2$) and landscape (3 × 3km) AES gradients in LandSpAES and in the scoped CitSci schemes, and the range in the number of sites surveyed across 2017 – 2019 (the number of sites surveyed varied with year for the CitSci schemes).

Dataset	Correlation between local and landscape AES gradients	Range in number of sites surveyed in 2017 - 2019
LandSpAES survey squares	0.35	54
Breeding Bird Survey	0.66	2302 - 2346
Wider Countryside Butterfly Survey	0.67	510 - 584
UK Butterfly Monitoring Scheme	0.62	879 - 996
BeeWalks	0.63	160 - 241
Pollinator Monitoring Scheme	0.65	30 - 33
Rothamsted Insect Survey moth traps	0.74	33

The six CitSci schemes differed substantially in the quantity of data available (Table 3.19), with the BBS being the largest scheme by far. The butterfly CitSci schemes also had substantial amounts of data, while only around 30 sites a year were surveyed on the smaller PoMS) and RIS moths schemes, and intermediate amounts for the BeeWalks scheme. For comparison, the LandSpAES project surveys 54 1km squares each year (Table 3.19).

The correlations between local and landscape AES gradients presented in the scoping results above for each CitSci scheme (Section 3.2) are summarized in Table 3.19, together with the equivalent correlation for the LandSpAES survey. As discussed in the Introduction (Section 1.2), the LandSpAES survey was designed to enable the effects of local and landscape AES gradients to be tested independently. Correlations between AES gradients are higher for all the scoped CitSci schemes than for LandSpAES, though for all except the RIS moth survey the correlations are moderate.

Three of the CitSci schemes included in the scoping exercise and the LandSpAES survey were designed to representatively survey a 1km^2 (Table 3.20), while the other three CitSci schemes survey areas that do not exactly match 1km grid squares. Both the AES gradient values and the habitat variables used in the scoping above are attributed to 1km grid squares, so there is more confidence that these will match the survey area for the CitSci schemes that are designed to survey 1km squares. For the three CitSci schemes not designed to survey 1km grid squares, the centroid of the transect route (UKBMS and BeeWalks) or the trap location (RIS moth survey) for each survey site were matched to a 1km grid square in order to attribute AES gradient values and habitat variables, but part of the survey area may fall outside the matched grid square. Therefore, there is lower confidence in the spatial matching of AES gradient values and habitat variables to the survey units for these three CitSci schemes.

Table 3.20 Summary of which CitSci schemes were designed to survey a 1km grid square

Survey designed to cover a 1km grid square	**Survey not designed to cover a 1km square**
LandSpAES Breeding Bird Survey Wider Countryside Butterfly Survey Pollinator Monitoring Scheme	UK Butterfly Monitoring Scheme BeeWalks Rothamsted Insect Survey moth traps

As a result of the scoping exercise, we decided to use all CitSci schemes except the RIS moth survey in the analytical work reported in the following sections. The RIS moth survey had only 33 sites with available data for the time period of interest (2017-2019) and showed a strong correlation between local and landscape AES gradients (Table 3.19), suggesting separating these effects would be difficult. There were also several differences in survey protocols meaning the responses derived would not be directly comparable between RIS moth traps and LandSpAES (Section 3.2.6).

Some concerns were flagged over the suitability of the Pollinator Monitoring Scheme (PoMS) data, due mainly to the low number of sites in this recently started scheme, and the moderate correlations found between AES gradients and some habitat variables (Section 3.2.5). Nonetheless, it was decided to try to include response variables calculated from PoMS data in the quantification of between-NCA differences and modelling described below. In conclusion, from the scoping work we did not use the RIS data in the next stages of analytical work, and did use the other five remaining CitSci schemes (WCBS, UKBMS, BeeWalk, PoMS and BBS).

4. Methodological overview

4.1 Calculation of taxon responses

For the selected CitSci schemes we calculated species response variables in the same way as for those used within the LandSpAES project. Slightly different sets of response variables were calculated for invertebrates and birds (Table 4.1). For invertebrates, we calculated total species richness, Shannon diversity index and total abundance for each 1km square for each taxonomic group. All metrics were summed across all visits to each 1km square per year. These metrics were reported on as "headline" community metrics in the LandSpAES project.

Table 4.1.1. Response variables used for each taxonomic group.

Taxonomic group	Relevant citizen science schemes	Key response variables for extrapolation
Butterflies	UKBMS WCBS	Species richness Shannon diversity index Total abundance
Bumblebees	BeeWalks (transects) PoMS (pan traps)	Species richness Shannon diversity index Total abundance
Hoverflies	PoMS	Species richness Shannon diversity index Total abundance
Solitary bees	PoMS	Species richness Shannon diversity index Total abundance
Birds	BBS	For each of all terrestrial species: Species richness Shannon diversity index Total abundance (omitting Jackdaw, Rook and Woodpigeon) For Farmland Bird Index species: Species richness Total abundance (omitting Jackdaw, Rook and Woodpigeon) For BoCC4 Red List species: Total abundance Abundance of exemplar farmland species: Skylark Lapwing Linnet Meadow Pipit Whitethroat Yellowhammer

For birds, we calculated the same headline metrics for both terrestrial and Farmland Bird Index species, and additionally assessed the abundance of six exemplar farmland bird species (Table 4.1), and total abundance of bird species on the BoCC4 Red List. Species-level responses were particularly important for birds because AES and conservation targets for birds are usually expressed at the species level rather than the community level. For birds, analyses of data from LandSpAES and BBS both use maximum counts per species per square across all visits made in a given year. Given the additional length of transect and numberof visits per year in LandSpAES, counts are therefore expected to be higher than those in BBS, but this should note affect variations in counts with respect to environmental influences.

For bird responses, preliminary exploration of BBS data showed that some survey squares with high total abundance and including habitats that are not well-represented in the NCAs surveyed in LandSpAES, often also involving species that are not targeted by relevant AES management. The rationale for LandSpAES was to calculate AES gradients that could be applied to the full range of management options thought to benefit target taxa, covering the full range of agricultural habitats in England. However, for the LandSpAES survey, resource limitations meant that six NCAs were selected for survey to represent the range of common types of English farmland and upland, and so the LandSpAES survey data relate to the AES options that are relevant to those habitats. It was inevitable that various habitat types, such as coastal and freshwater habitats, would not be found within those NCAs, although some of them will be managed using AES options. These habitats will often host different biological communities to those in the farmland types that LandSpAES has considered, but some are still farmed and some AES options that are applied to them, such as those for grassland management, are also applied elsewhere. Hence, although the same options may be present, it is likely that relationships with taxon responses will be different because the analyses would be extrapolating to a different species pool and background habitat context. This provides an argument for filtering particular species or habitats from the data before calculating assemblage metrics. However, to achieve maximum representation, we begin with the assumption that underlying relationships between AES scores and taxon metrics are consistent across landscapes, removing potential problem data as described below. Deviations from this assumption could cause a problem where CitSci data sets are larger and cover a wider range of habitats, so there is more potential for relationships with farmland to be obscured. Therefore, this is more of a potential issue for birds than for other taxa in this study. Moreover, for birds, there is no theoretical basis, overall principle or conservation target involving simple species richness or total abundance across all species, unlike for pollinators, for example. This means that there is less reason, a priori, to support extrapolation beyond the species and habitat ranges of the LandSpAES source data.

The potential problems with representativeness and uninformative high abundances in BBS were addressed by removing data from habitats that are poorly represented by the LandSpAES models. These were coastal squares (those that contain non-zero areas of coastal land cover broad habitats), in addition to those squares already filtered out during AES gradient calculations with >50% woodland and those with >30% urban or freshwater habitats (see Section 2.2). Flocking behaviour of species such as Woodpigeon, Jackdaw and Rook means that their numbers could dominate and distort bird community responses. Due to this, these species were omitted from total abundance counts. In addition, large groups (>50 individuals) of Starling and Carrion Crow are removed from the data for abundance measures, since these will almost certainly not consist of locally breeding, adult individuals. Overall, however, we selected a species list for analysis which includes all terrestrial breeding bird species that were present.

4.2 Ordination of environmental covariates

A key aim of this project was to increase comparability in estimation of AES gradient effects for areas not surveyed under LandSpAES, by replacing the random term for NCA identity used in LandSpAES models with environmental covariates that explained the between-NCA differences. A model fit with these covariates instead of the NCA term should be much easier to use to extrapolate outside the surveyed NCAs, because we chose relevant covariates where data was available for all 1km squares in England.

We identified 28 environmental variables extracted from the datasets listed in Table 2.2 that could potentially be included in models of species responses (Table 4.2).

Table 4.2.1. Environmental covariates extracted for use in modelling work.

Environmental covariate (all calculated per 1km)	**Data source**	**Notes**
Mean elevation (m. asl)	IHDTM[1]	
Elevation variability (standard deviation)	IHDTM	
Mean rainfall (kg m^{-2} s^{-2})	CHESS-met 2011-2015	
Rainfall variability (standard deviation)	CHESS-met 2011-2015	
Mean temperature (K)	CHESS-met 2011-2015	
Temperature variability (standard deviation)	CHESS-met 2011-2015	
Length of hedgerows (m)	Woody Linear Features Framework	
Mean slope (mean tangent)	IHDTM	
Aspect: southness (mean(-cos(radians)))	IHDTM	
Aspect: eastness (mean(sin(radians)))	IHDTM	
Parent material grain size	BGS Soil Parent Material	Each category was assigned the median grain size
Carbonate content	BGS Soil Parent Material	Coded as either none (0), low (0.5) or moderate to high (1)
Area of Severely Disadvantaged Area (SDA) land (m^2)	LFA	
Area of arable land (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	
Area of broadleaved woodland (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	
Area of coniferous woodland (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	

Environmental covariate (all calculated per 1km)	**Data source**	**Notes**
Area of improved grassland (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	
Area of semi-natural grassland (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	Defined as area of calcareous grassland, neutral grassland, fen, marsh swamp, heather grassland and heather
Area of calcareous and neutral grassland (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	
Area of fen, marsh and swamp (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	
Area of heather and heather grassland (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	
Area of mountain, bog and heath (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	Defined as area of heather, heather grassland, bog and inland rock
Area of coastal habitats (m^2)	Land Cover Map 2015, 2017, 2018 and 2019	Defined as area of supra-littoral rock, supra-littoral sediment, littoral rock, littoral sediment and saltmarsh
Area of mass flowering crops (m^2)	UKCEH Land Cover® *plus*: Crops 2015, 2016, 2017, 2018 and 2019	Defined as area of oilseed rape, field beans, potatoes and beet
Area of spring cereals (m^2)	UKCEH Land Cover® *plus*: Crops 2015, 2016, 2017, 2018 and 2019	Defined as area of spring barley and spring wheat
Area of winter cereals (m^2)	UKCEH Land Cover® *plus*: Crops 2015, 2016, 2017, 2018 and 2019	Defined as area of winter barley, winter wheat and winter oats
Area of maize (m^2)	UKCEH Land Cover® *plus*: Crops 2015, 2016, 2017, 2018 and 2019	
Area of broadleaf crops (m^2)	UKCEH Land Cover® *plus*: Crops 2015, 2016, 2017, 2018 and 2019	Defined as area of oilseed rape, field beans, potatoes, beet and peas

[1] IHDTM = integrated hydrological digital terrain model. All IHDTM data from https://www.ceh.ac.uk/services/integrated-hydrological-digital-terrain-model

Initial exploratory work aimed to reduce this list of 28 potential variables to a smaller subset that we could use in the modelling to replace the NCA random term. To identify the variables most strongly linked to variation between NCAs, we conducted a Principal Components Analysis (PCA) using average values calculated for each NCA. We also included five additional variables only available averaged or summed across the NCA (bird species pool size, butterfly species pool size, NCA size, minimum elevation and maximum elevation). We found that the primary axes of variation in the NCAs were related to variables such as rainfall and area of arable (Figure 4.2.1) but that many variables could potentially be included in the species models to replace the NCA term.

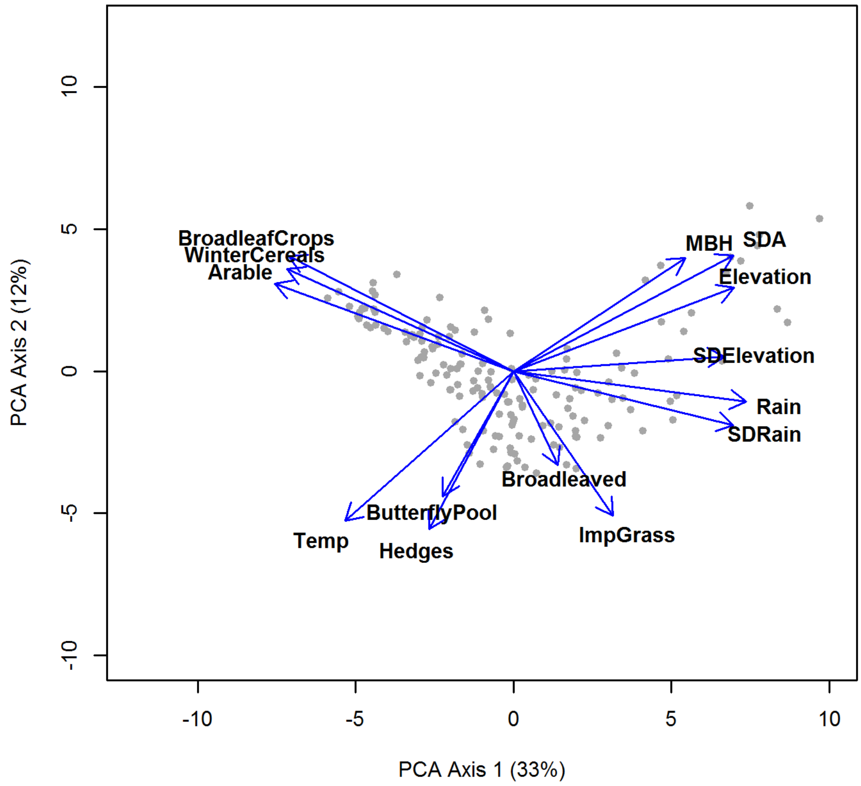

Figure 4.2.1. Ordination of all NCAs based on 33 environmental variables (those shown in Table 4.2.1 plus NCA size, butterfly species pool size, bird species pool size, minimum elevation and maximum elevation; all covariates only available at NCA level). The first two PCA axes are shown. Only a subset of the environmental variables included are shown for clarity.

To avoid subjective selection of a smaller number of environmental covariates to include in species response models we decided instead to refit the ordination at a 1km square level, and use the ordination axes themselves in the species response models. The benefit of this approach is that the first few PCA axes should reflect the majority of variation so that we can describe environmental variation using a small number of PCA axes. The cost of using PCA axes is that they are no longer easily interpretable in relation to the original environmental covariates. In this project we aimed to use PCA axes to account for environmental variation between survey squares previously captured by an NCA random effect, rather than to understand the relationships between the response and environment. Therefore, we considered that using PCA axes instead of environmental covariates to be an appropriate solution.

The ordination fit at the 1km level showed broadly similar patterns to that fit at NCA level (Figure 4.2.2), with the first two PCA axes explaining 26% and 12% of variation respectively.

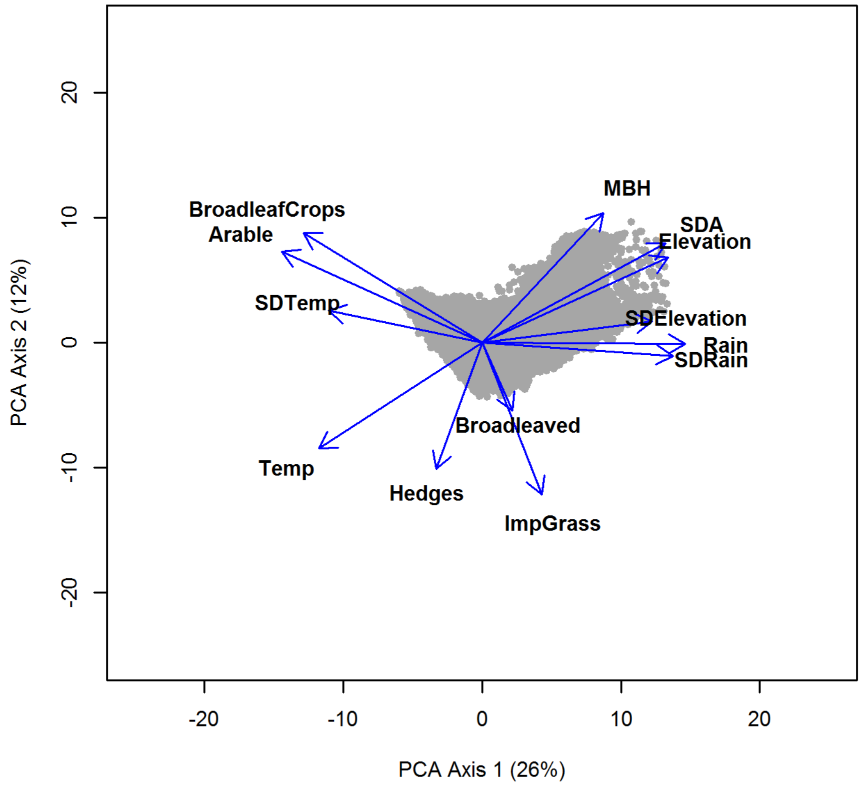

Figure 4.2.2. Ordination of all 1km squares in England based on 28 environmental variables shown in Table 4.2.1. The first two PCA axes are shown. Only a subset of the environmental variables included are shown for clarity.

4.3 Individual CitSci scheme models

To explore whether relationships found between AES gradients and taxa responses for the LandSpAES project were similar outside of the six NCAs surveyed under LandSpAES there were three initial steps applied to the LandSpAES and CitSci datasets separately. Firstly, we defined a core model based on the structures used in the LandSpAES project and selected an appropriate response variable distribution.

Secondly, we used the PCA axes calculated as described in Section 4.2 to replace the NCA term in the LandSpAES models. This allows more direct application of the LandSpAES models to new areas by replacing a random term, which cannot be estimated in unsurveyed NCAs, with a set of fixed effects which are known in all 1km squares.

Thirdly, we assessed the similarity of AES responses in models fitted to LandSpAES data with models fitted to CitSci data. If the responses to local (1km) and landscape (3km) AES gradients are similar between LandSpAES and the relevant CitSci scheme then this gives us high confidence that the LandSpAES results are representative of national patterns, beyond the six surveyed NCAs.

4.3.1 Core model structure

For each response variable listed in Section 4.1 we constructed a core model (Eq 1) which included the local and landscape AES gradients, a fixed effect of year and any other scheme-specific terms needed to account for within-scheme variation in sampling effort. For example, the number of visits was highly variable in UKBMS so an additional term was added to the models to account for variation in responses caused by varying numbers of visits to the UKBMS squares. Terms to account for varying effort were also included in LandSpAES models to account for a few missing spring 2017 surveys. For this project, we did not include an NCA random effect in the models of LandSpAES data.

$$\text{Response} \sim \text{AES1KM} * \text{AES3KM} + \text{year} + \text{effort} \qquad \text{(Eq 1)}$$

At this stage we also defined an appropriate error distribution to use for each response variable. For richness and abundance responses either a Poisson or a negative binomial distribution was used. These distributions are appropriate for count data and the negative binomial structure can be used if there is evidence of overdispersion in the data (where the variance is greater than the mean), which the Poisson distribution cannot account for (Bolker, 2008). For Shannon diversity responses we used a normal distribution, transforming the response if required to meet the assumptions of the model. If we used a transformation for a response in one dataset (e.g. an exponential transform for hoverfly diversity in LandSpAES) then we aimed to use the same transformation in the corresponding comparison dataset (e.g. an exponential transform for hoverfly diversity in PoMS) to simplify comparisons of the model outputs. We checked for collinearity of predictors using variance inflation tests.

4.3.2 Selection of PCA axes

For each response model we then added PCA terms to the core model structure. We added the first two PCA axes to all models and then tested whether further terms were required based on AIC. If adding a further PCA axis reduced AIC by 10 or more, then we included this axis in the model. To help automate this process we used the ‘addterm’ function in the MASS package of R. We selected a quite high AIC cutoff of 10 to ensure terms were only added when they made a substantial improvement to the model (Burnham & Anderson, 2004). We did not place any restrictions on which PCA axes were included, as we hypothesized that a taxon could respond to an axis that does not explain a great deal of variation across all squares. For example, a final model could look something like Eq 2.

$$\text{Response} \sim \text{AES1KM} * \text{AES3KM} + \text{year} + \text{effort} + \text{axis 1} + \text{axis 2} + \text{axis 16} \qquad \text{(Eq 2)}$$

By selecting PCA axes to include on a per-response variable basis, we did not select the same PCA axes for each response variable. This is appropriate as different response variables may be affected by different elements of environmental variation, due to the ecology of the taxa.

We placed different cutoffs on the total number of PCA axes to include based on the amount of data available for each dataset. For the small datasets (LandSpAES and PoMS) a maximum of 3 additional PCA axes were included in addition to axes 1 and 2. For the

WCBS, UKBMS and BeeWalk datasets a maximum of 6 PCA axes were included. For the BBS dataset no maximum was set as the dataset was so large.

To validate that the addition of the PCA terms appropriately accounted for variation previously attributed to NCA we checked two things:

1. Did the model with PCA axes added have similar or lower AIC to one with an NCA random effect? This gives us an indication of whether a model with PCA axes is a similar or better model at efficiently explaining variation in the response
2. For LandSpAES models only, does replacing the NCA term with PCA axes change estimated relationships with other core model terms? This might indicate that the PCA axes are explaining variation previously attributed to AES effects.

4.3.3 Comparison between LandSpAES and CitSci schemes

Once the PCA terms were included in both LandSpAES and CitSci species response models, we could then compare the relationships with AES gradients seen in LandSpAES to those seen in the CitSci schemes. We would not expect estimated coefficients to be identical, but if both LandSpAES and CitSci schemes were reflecting a shared underlying pattern of taxa response to AES gradients, we would expect coefficients to have the same magnitude and sign (direction of relationship).

We applied a formal test of coefficient similarity (z-test) to all combinations of LandSpAES and CitSci models to check whether the coefficients were statistically different or not. This test considers both the estimate of the coefficient and the standard error around the estimate. The z-test was applied to each of the AES terms (local, landscape and interaction). We considered a combination of models to ‘pass’ the test if all three coefficient comparisons produced p value of more than 0.05 (no significant difference between models).

For the BBS scheme we found that standard errors on coefficients were very small due to the very high statistical power resulting from the large sample size and therefore few models passed the z-test. We therefore expanded the consideration of which models to take through to the integrated modelling to those with borderline passes.

4.4 Integrated models

For responses where we found good evidence that relationships with the AES gradients were similar between LandSpAES and CitSci schemes, we considered integrated models. Integrated models use data from two or more datasets in a single model to estimate model parameters. The potential advantage of integrating data is that we can obtain consistent estimates of effects across multiple datasets, and these estimates can therefore have reduced uncertainty and wider direct relevance, compared to models using single datasets. In the context of extrapolation of LandSpAES results, using an integrated approach may allow us to investigate AES gradient effects with reduced uncertainty compared to using LandSpAES data alone as well as quantifying AES effects consistent across schemes and hence can be considered to be representative of larger (national) scales.

The challenge in integrating datasets is that different datasets may observe slightly different species responses, due to differences in sampling design, survey method or spatial coverage, even when measuring fundamentally the same response. For example in bumblebee transect recording, LandSpAES uses a larger moving box than BeeWalk (5 × 5 × 5m in LandSpAES, 4 × 4 × 4m in BeeWalk). Therefore, we might expect LandSpAES to record a higher species richness and abundance across a 1km square than BeeWalk. Other differences between the schemes also exist that could affect the species response observed, for example some CitSci survey areas are not restricted to a 1km grid square (Section 3.3) and therefore it may be harder to link responses to local and landscape AES gradients as well as the PCA scores which all link to a focal 1km square.

To account for these differences we used a framework that allows multiple elements of survey design or protocol to vary between schemes without having to attribute differences in species response between schemes to particular survey elements. In the BeeWalk example, we can account for differences between LandSpAES and BeeWalk without having to attribute them to differences in moving box size or transect placement. This framework is useful as, in most cases, we do not have enough information to tell us which difference between the LandSpAES and CitSci scheme design or protocol resulted in a difference in species responses.

We developed two model structures that could be used to integrate LandSpAES and CitSci data. In the first we allowed LandSpAES and CitSci surveys to have different average species responses (e.g. different total abundances of bees) but assumed that the relationships with AES gradients were identical between surveys (Eq 3). In the second, more complex, model we allowed both the average species response and the relationships with AES gradients to vary between surveys (Eq 4). This model is more difficult to fit but accounts for surveys observing slightly different relationships with AES, which may be useful if e.g. the CitSci scheme survey unit is not restricted to a 1km grid square or if the schemes capture different regions of the AES gradient.

Response ~ AES1KM*AES3KM + other model terms + (1|Survey) (Eq 3)

Response ~ AES1KM*AES3KM + other model terms + (AES1KM*AES3KM|Survey) (Eq4)

In Eq 3 and Eq 4 terms in brackets indicate a random effect. The term (1|Survey) indicates a random intercept is used, allowing average species responses to vary between LandSpAES and CitSci. The term (AES1KM*AES3KM|Survey) indicates random intercepts and random slopes are fitted. A model with this term allows both the average species response and the relationships with local (1km) and landscape (3km) AES to vary between LandSpAES and CitSci surveys. In the random slope model all three AES terms (local, landscape and interaction) are allowed to vary by survey. Including random slopes makes the model in Eq 4 much more difficult to fit.

The ‘other model terms’ in Eq 3 and 4 indicate the other components of the core model structure and the PCA axes (cf. Eq 2). Where different sets of PCA axes were selected for LandSpAES and CitSci individual scheme models, all selected PCA axes were included in the integrated model.

4.5 Model evaluation

We evaluated the integrated and LandSpAES models using three metrics; median absolute error (MAE), root mean square error (RMSE) and coefficient of variation (CV). These three metrics capture slightly different elements of overall model performance. The MAE and RMSE are helpful to understand absolute errors of the model and can be interpreted as “plus or minus” response units. For example, a RMSE of 5 for an abundance model would indicate that on average the predicted abundance would be out by about 5 individuals compared to the actual numbers. The CV is the RMSE scaled relative to the mean response variable, accounting for the fact that an error of 5 individuals when the mean count is 10 would be interpreted differently than when the mean count is 1000. In all cases, the lower the value of the metric, the better the model.

Another element of uncertainty of interest in this project is precision around the estimated AES effects. We can evaluate this by looking at the standard errors around the estimates. The smaller the error the higher the precision and therefore the more confidence we have in the AES trends.

5. Results by taxonomic group

5.1. Birds

Widespread breeding birds in terrestrial environments are recorded by the citizen science scheme the *Breeding Bird Survey* (BBS), which is run by the British Trust for Ornithology (BTO) and funded by BTO, the Joint Nature Conservation Committee and the Royal Society for the Protection of Birds.

5.1.1 Accounting for protocol differences

5.1.1.1 Number of visits and lengths of transect

The BBS is designed to monitor variation in abundance at large scales and over the long term, using a low-intensity survey approach, rather than proving detailed data on local abundance. Therefore, the LandSpAES sampling design doubled the number of visits per season (from two to four) and increased the spatial coverage by 50% (from 2km of transect to 3km), but other elements of the protocols are similar. Therefore, both species richness and abundance variables based on maximum counts would be expected to be higher in LandSpAES than in BBS, despite the common sampling unit of the 1km square. However, it is clear that baseline bird assemblage composition and species' abundances will vary between survey squares, and the focus of this project is on prediction of changes in biodiversity response variables in response to AES management, not on estimating absolute densities. Hence, we consider that the protocol differences are not important for the modelling, and that the average LandSpAES square, from the perspective of the models, can be considered equivalent to a BBS square with a relatively rich and abundant bird community for the sample.

5.1.2 Explaining NCA variation

The PCA axis approach, described in Section 4.3 was used to identify a number of axes best explaining the variation previously attributed to the NCA for each response. For LandSpAES data, we included up to five PCA axes (always including the first two), but for models using BBS data, there was no limit to the number of axes that could be added beyond the first two PCA axes, because sample sizes supported the inclusion of many more axes in practice (Table 5.1.1).

Table 5.1.1. Selected PCA axes for each response variable.

Response variable	**PCA axes selected**	
	LandSpAES	**BBS**
Bird abundance	1, 2, 6	1, 2, 3, 12, 13, 15, 21, 26
Bird richness	1, 2, 15, 18, 28	1, 2, 4, 5, 7, 13, 15, 16, 18, 19, 20, 21, 23, 25, 27
Bird diversity	1, 2, 15, 18, 28	1, 2, 3, 4, 5, 6, 13, 15, 17, 19, 20, 23, 25, 28
Red List Bird abundance	1, 2, 3, 22	1, 2, 3, 4, 5, 6, 8, 9, 12, 15, 17, 18, 21, 22, 23, 26
FBI Bird abundance	1, 2, 16	1, 2, 3, 4, 5, 8, 9, 12, 15, 17, 18, 21, 22, 23
FBI Bird richness	1, 2	1, 2, 5, 8, 12, 15, 16, 18, 19, 20, 23, 24, 25, 26

5.1.3 Results of individual scheme models

We compared the relationships with AES gradients seen in LandSpAES to those seen in BBS by exploring the estimated coefficients. Given the sample size difference between the datasets, differences in relationships with AES were likely to occur, so whilst not anticipating these to be identical, we determined that coefficients with similar slopes showed a shared core pattern (sign and direction) of a response to AES gradients. Such patterns are independent of power, due to the large sample sizes in BBS data. In addition, we conducted a formal test of coefficient similarity (z-test; Section 4.3). We applied the z-test to all models and each AES term within these (Appendix 2 Table A7). A drawback of this approach is that no two datasets will ever be identical, and the ability of the test to detect a difference depends on both the size of the difference and the sample size: with a sufficiently large sample, any difference would be detectable. Hence, due to the high power arising from the large sample size in BBS data, very few models passed the z-test for birds. This was despite, in some cases, the underlying patterns with respect to AES sharing the same direction as the corresponding LandSpAES model. The test is fundamentally designed to reveal whether two values are really different, as opposed to whether they are essentially the same, which is a question of judgement. Therefore, when comparing results from LandSpAES and BBS models, we focus on shared relationships with AES gradients, looking for parallel slopes for estimated coefficients, as opposed to relying only on the Z test results.

Table 5.1.2. Estimated relationships between bird response variables and AES gradients for LandSpAES and BBS. Estimated coefficients are shown ± standard error.

Model	Local (1km)	P	Landscape (3km)	P	Interaction	P
BBS abundance	-0.007 ± 0.009	0.434	-0.026 ± 0.008	0.001	0.008 ± 0.005	0.119
LandSpAES abundance	0.112 ± 0.057	0.051	-0.013 ± 0.033	0.695	-0.096 ± 0.051	0.061
BBS richness	0.01 ± 0.005	0.030	0.008 ± 0.004	0.058	0.003 ± 0.003	0.277
LandSpAES richness	0.097 ± 0.035	0.005	0.003 ± 0.02	0.888	-0.09 ± 0.032	0.004
BBS diversity	0.301 ± 0.088	0.001	-0.015 ± 0.08	0.848	0.056 ± 0.051	0.273
LandSpAES diversity	1.251 ± 0.731	0.090	1.149 ± 0.416	0.007	-1.977 ± 0.639	0.002
BBS Red List abundance	-0.039 ± 0.015	0.008	-0.017 ± 0.013	0.205	0.031 ± 0.009	<0.001
LandSpAES Red List abundance	0.285 ± 0.087	0.001	0.069 ± 0.054	0.203	-0.278 ± 0.079	<0.001
BBS FBI abundance	-0.013 ± 0.014	0.364	-0.006 ± 0.013	0.621	0.021 ± 0.008	0.008
LandSpAES FBI abundance	0.373 ± 0.089	<0.001	-0.027 ± 0.054	0.610	-0.234 ± 0.084	0.005
BBS FBI richness	-0.004 ± 0.007	0.541	0.019 ± 0.006	0.003	0.006 ± 0.004	0.159
LandSpAES FBI richness	0.106 ± 0.052	0.043	-0.04 ± 0.033	0.230	-0.07 ± 0.051	0.167

5.1.3.1 Bird species abundance

Due to the flocking behaviour of Woodpigeon, Jackdaw and Rook, which means that their numbers could dominate and distort bird community responses, these species were omitted from total abundance counts. In addition, large groups (>50 individuals) of Starling and Carrion Crow were filtered from the data, since these will almost certainly not consist of locally breeding, adult individuals.

For bird abundance at the local gradient scale, the relationships with AES gradient in the LandSpAES and BBS were contrasting, with a significant positive relationship in LandSpAES and a non-significant negative relationship in BBS. However, at the landscape (3km) scale, both surveys showed a negative relationship between abundance and AES gradient score (Figure 5.1.1). Figure 5.1.2 shows an interaction plot between local and landscape level AES scores, and bird abundance. From this we can see a negative interaction in the LandSpAES data, but a positive one for the BBS, and this is confirmed by the results in Table 5.1.2, where we see a non-significant positive relationship in the BBS data, and a near-significant negative relationship in the LandSpAES data.

We notice that, in LandSpAES, the mean abundance is higher than that from BBS survey squares. This is probably a consequence of the survey effort, where LandSpAES surveys cover 50% more length of transect, so will tend to count more birds, and consists of four visits per year (cf. BBS surveys with two visits per year), so larger counts are more likely to be recorded for all species (and greater species richness) with LandSpAES. The BBS monitors variation at larger scales with a low-intensity approach, whilst LandSpAES provides more detailed data on local abundance as well as having a 50% increase in survey area (3km of transect instead of 2km). Other elements of the protocol are similar, however.

Bird abundance therefore does not appear to be a good candidate for an integrated model using BBS and LandSpAES, as evidence shows that responses are not similar across the surveys.

Figure 5.1.1. Predicted relationships between bird abundance and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

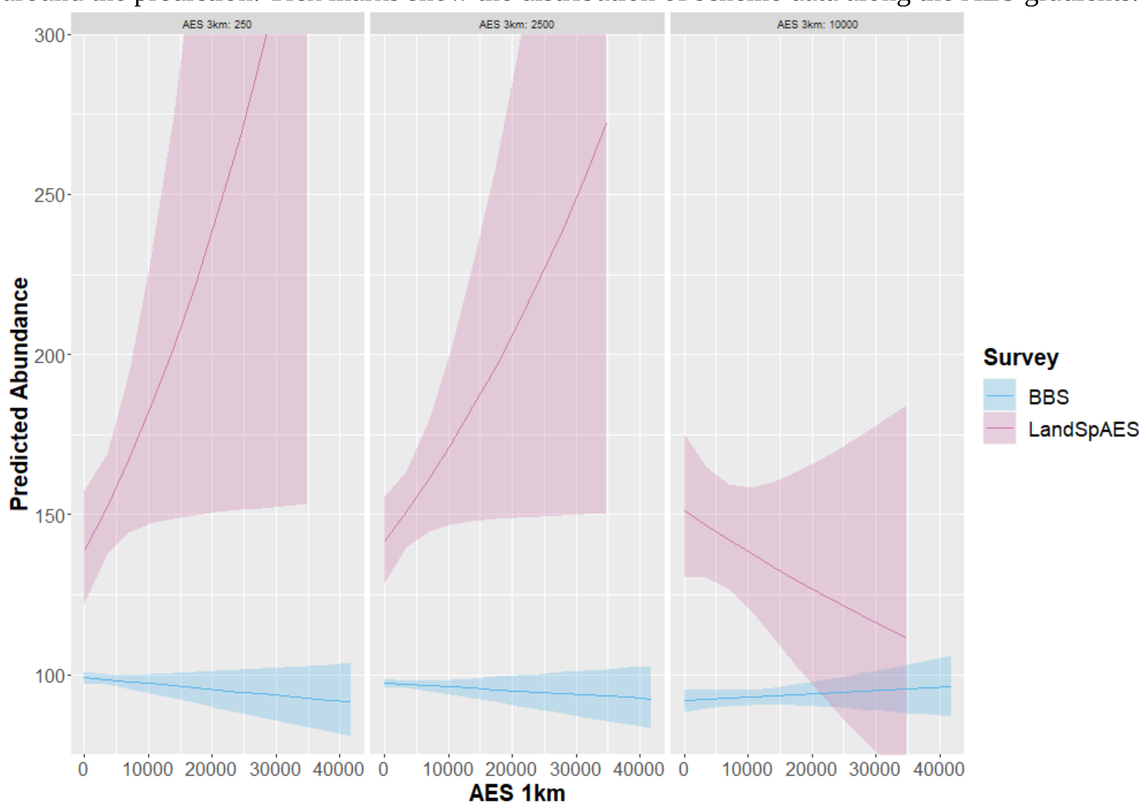

Figure 5.1.2. Predicted relationship between bird abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.3.2 Bird species richness

In bird richness, we saw some similar relationships between the LandSpAES and BBS surveys. Both at the local (1km) level and landscape (3km) level, there were positive relationships between richness and AES gradient score in both surveys (Figure 5.1.3). There was, however, a negative interaction term for the LandSpAES data, whilst the BBS data maintained a positive relationship. In LandSpAES, relationships were significant at the 1km level and for the interaction, and in BBS, these relationships were significant at the 1km and 3km levels, but not for the interaction (Table 5.1.2). At low and medium landscape (3km) AES gradients, both LandSpAES and BBS showed a positive association between local (1km) AES and species richness (Figure 5.1.4). For the higher landscape score considered, the relationship between local AES and richness in LandSpAES data was, however, negative.

As described, both in LandSpAES and BBS relationships at the local (1km) level were positive. However, the estimated effect of this local AES in LandSpAES was far stronger, shown by the steeper, positive line in Figure 5.1.3, whilst the trend in the BBS data was much shallower, but still positive. Although these responses showed the same trend in terms of direction, a z-test comparing the similarity between coefficients indicated that they were significantly different ($z=2.478$, $p=0.013$, Appendix 2 Table A7). The z-test also confirmed dissimilar relationships for the interaction term, which were, critically, in both magnitude and direction ($z=-2.924$, $p=0.003$), suggesting a fundamental difference in the relationships with AES scores between the data sources, albeit a more subtle one than for abundance.

Therefore, bird species richness is not a suitable candidate to take forwards to integrated modelling since the interaction term in the LandSpAES model, and the interaction term in the BBS model, had dissimilar slope directions.

Figure 5.1.3. Predicted relationships between species richness and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

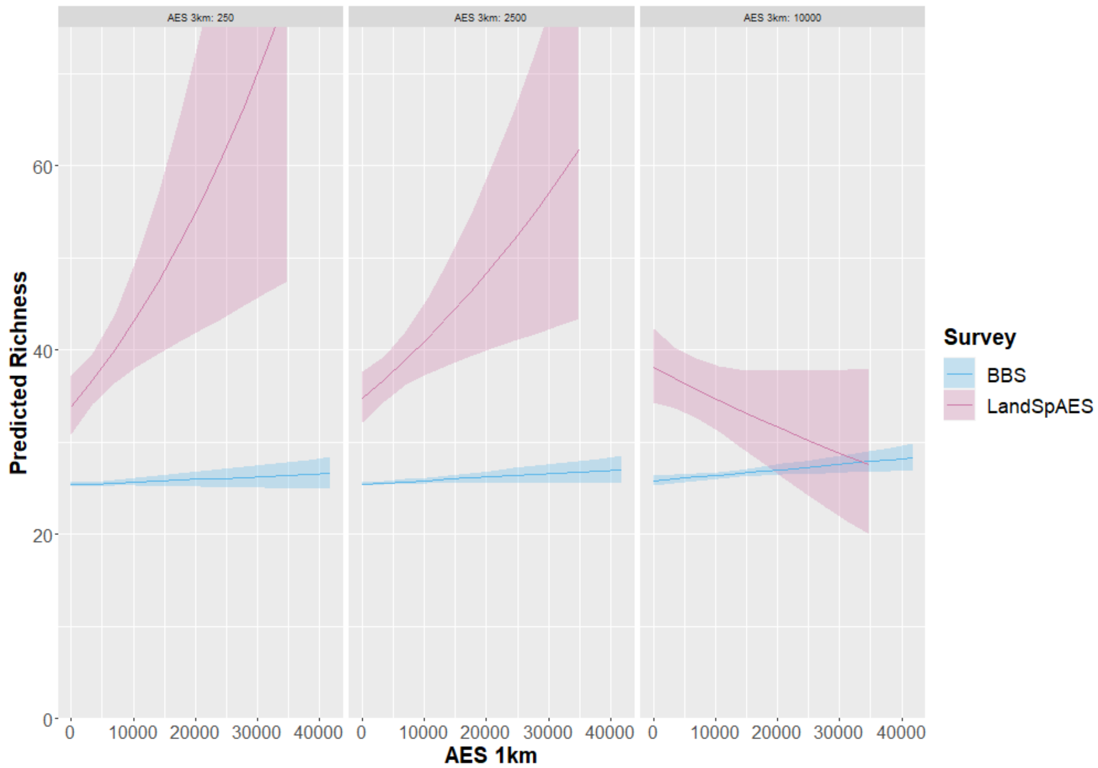

Figure 5.1.4. Predicted relationship between bird species richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.3.3 Bird diversity

The Shannon diversity indices across LandSpAES and BBS surveys showed similar relationships at the local (1km) level, but differed at the landscape (3km) level, and for the interaction. At the local level, the relationships were both positive and significant. At the 3km level in BBS, the relationship was very weakly negative whilst in LandSpAES it was positive and significant (Figure 5.1.5). The opposite relationship applied for the interaction, where in LandSpAES the relationship was negative and significant, and in BBS positive and non-significant (Table 5.1.2). For three different landscape AES scores, Figure 5.1.6 shows relationships between diversity and local AES in the LandSpAES and BBS data. We can see that, for low and medium 3km AES gradients both schemes showed a positive trend, whereas for a high 3km score, the LandSpAES data showed a steep negative association. This is similar to the trends seen for species abundance and richness.

Diversity is not an appropriate response to take forward into integrated modelling, since relationships differed between LandSpAES and BBS data at the 3km scale and for the interaction.

Figure 5.1.5. Predicted relationships between diversity (exponential transformed Shannon index) and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

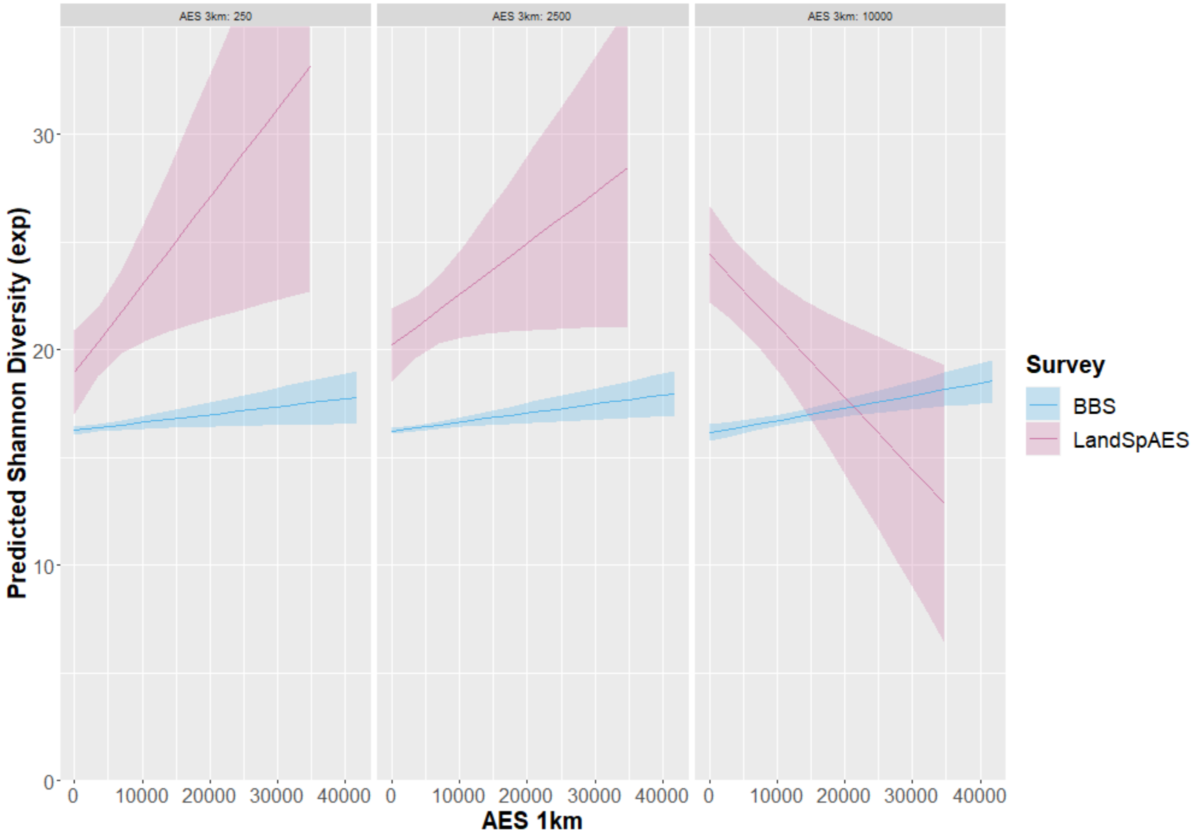

Figure 5.1.6. Predicted relationship between diversity and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.3.4 Farmland Bird Indicator (FBI) species abundance

The 19 Farmland Bird Indicator (FBI) species are the following: Corn Bunting, Goldfinch, Greenfinch, Grey Partridge, Jackdaw, Kestrel, Lapwing, Linnet, Reed Bunting, Rook, Skylark, Starling, Stock Dove, Tree Sparrow, Turtle Dove, Whitethroat, Woodpigeon, Yellow Wagtail, and Yellowhammer. Here, we summed counts for these species, but omitting Jackdaw, Rook and Woodpigeon, and high counts (>50) of Starling, due to the flocking behaviour of these species (potentially dominating abundance values) and the likelihood that groups contain non-breeding individuals.

At the 1km local level, abundance of FBI species in LandSpAES data showed a positive significant relationship with AES gradient score. In BBS on the other hand, the association was negative, but non-significant (Figure 5.1.7). At the landscape (3km) scale, both LandSpAES and BBS showed a negative and non-significant association with FBI species abundance (Figure 5.1.7). The interaction term was non-significant for both surveys, but positive in BBS and negative in LandSpAES (Table 5.1.2). Figure 5.1.8 showed no similarity between predictions of abundance at the local (1km) scale for three different landscape (3km) AES gradients.

Since relationships were dissimilar between BBS and LandSpAES predictions for FBI species abundance, we did not produce an integrated model.

Figure 5.1.7. Predicted relationships between FBI species abundance and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

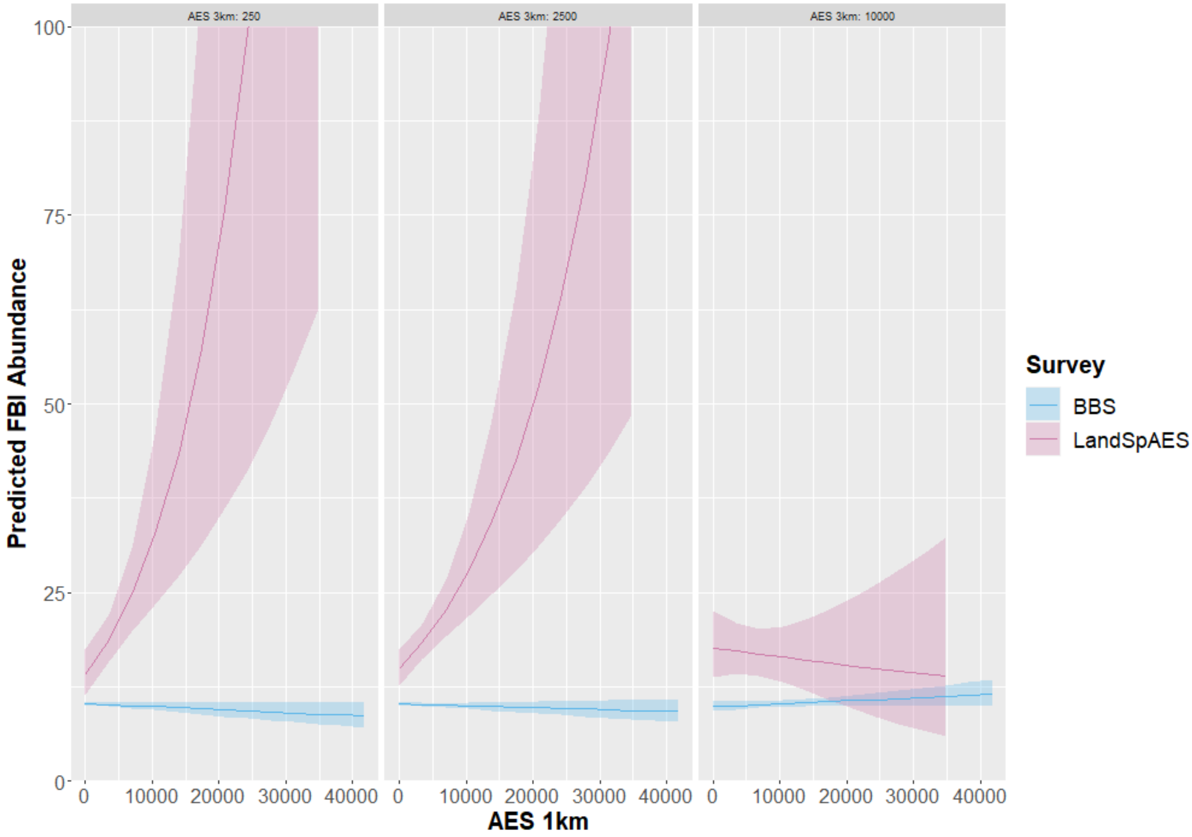

Figure 5.1.8. Predicted relationship between FBI species abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.3.5 Farmland Bird Indicator (FBI) species richness

All 19 Farmland Bird Indicator species are included in the richness metrics.

For FBI species richness, relationships between both local and landscape AES gradients were not similar across the two surveys. Additionally, the interaction term had contrasting signs between LandSpAES and BBS surveys (Table 5.1.2). For the LandSpAES data, the relationship between FBI species richness and local AES was significant and positive, whilst at the 3km scale and for the interaction we had negative, non-significant relationships. For BBS at the local (1km) scale, the association between richness and AES gradient score was negative and non-significant, whilst at the landscape (3km) scale we had a significant positive relationship. We can see such contrasting relationships in Figures 5.1.9 and 5.1.10. In the latter, we show the predicted relationship between FBI species richness and local level AES score for three different landscape gradient scores, and here we can see the dissimilar predicted richness responses.

Due to contrasting relationships, the FBI species richness models are not appropriate to take forward for integrated modelling.

Figure 5.1.9. Predicted relationships between FBI species richness and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

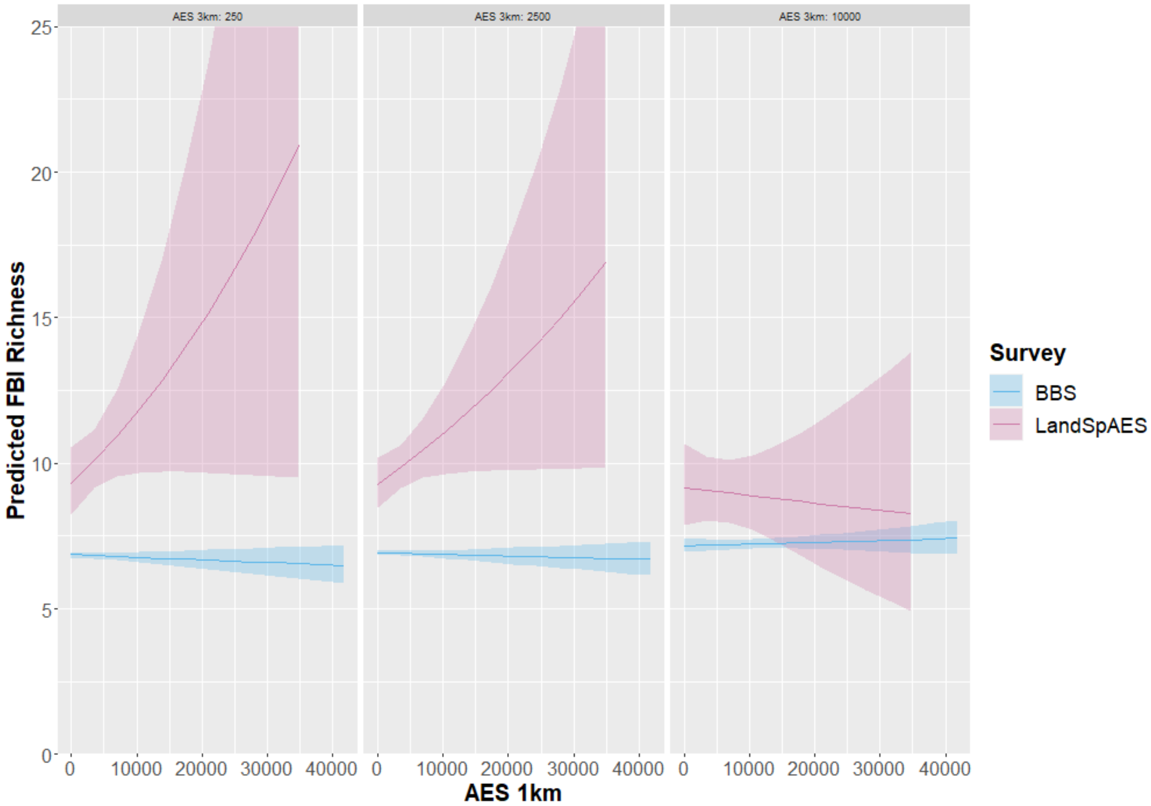

Figure 5.1.10. Predicted relationship between FBI species richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.3.6 Red List species abundance

Species on the Birds of Conservation Concern (BoCC4) list, defined with the status 'Red', were considered in models using LandSpAES and BBS data.

Red listed species abundance in BBS data had a negative relationship with AES gradient score at both the local (1km) and landscape (3km) levels, whilst in the LandSpAES data, these relationships were both positive (Figure 5.1.11). The interaction terms also contrast with each other, with a negative association in LandSpAES and a positive relationship in BBS (Table 5.1.2). In Figure 5.1.12 we can see that predicted relationships between red list species abundance and local level AES score were contrasting between data sets at three different landscape gradients.

The abundance of Red List species is therefore not appropriate to consider as an integrated model between LandSpAES and BBS data.

Figure 5.1.11. Predicted relationships between red list species abundance and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

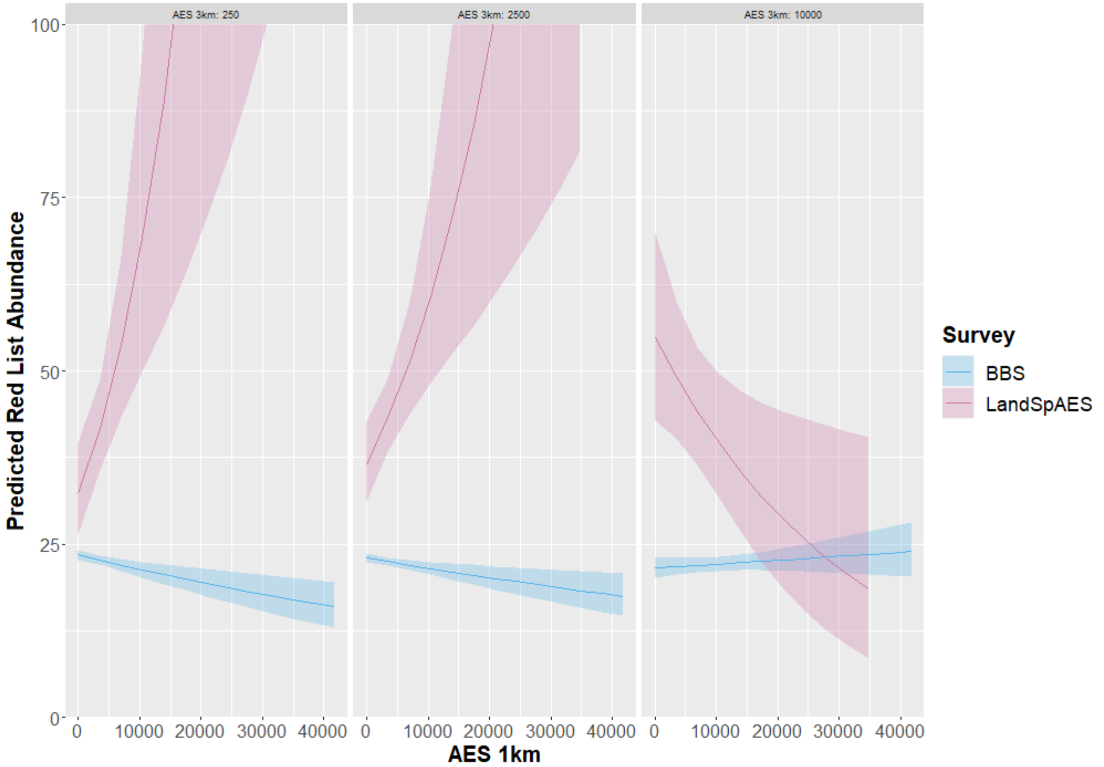

Figure 5.1.12. Predicted relationship between Red List species abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.3.7 Results for individual species abundances

We explored the abundance of six individual keystone species across both LandSpAES and BBS surveys. These species were selected to be representative of a range of habitat preferences and ecologies / guilds: Lapwing, Linnet, Meadow Pipit, Skylark, Whitethroat and Yellowhammer. Where survey squares fall outside the gross geographical ranges of individual species, the zero counts there do not inform about habitat relationships, so such squares were omitted. They were identified, for both data sets, by NCA: zero counts were included only for squares in NCAs where there was a non-zero count in one or more years for another square. Therefore, we will have different coverages of AES gradients between individual species, and this can be seen by the distribution of AES scores shown by rug plots in the following section. The models fitted are summarized in Tables 5.1.3 and 5.1.4.

Table 5.1.3. Estimated relationships between single species abundances and AES gradients for LandSpAES and BBS. Estimated coefficients are shown ± standard error.

Model	Local (1km)	P	Landscape (3km)	P	Interaction	P
BBS Lapwing	0.378 ± 0.005	<0.001	-0.448 ± 0.008	<0.001	0.019 ± 0.004	<0.001
LandSpAES Lapwing	-2.054 ± 0.914	0.914	0.938 ± 0.901	0.918	1.397 ± 0.157	0.930
BBS Linnet	-0.042 ± 0.005	<0.001	0.129 ± 0.004	<0.001	0.009 ± 0.003	0.001
LandSpAES Linnet	0.520 ± 0.187	0.006	-0.132 ± 0.118	0.264	-0.447 ± 0.182	0.016
BBS Meadow Pipit	0.143 ± 0.006	<0.001	-0.008 ± 0.005	0.108	-0.027 ± 0.003	<0.001
LandSpAES Meadow Pipit	0.480 ± 0.149	0.002	-0.031 ± 0.057	0.585	-0.28 ± 0.098	0.005
BBS Skylark	-0.025 ± 0.003	<0.001	0.081 ± 0.002	<0.001	0.032 ± 0.001	<0.001
LandSpAES Skylark	0.369 ± 0.087	<0.001	0.042 ± 0.0360	0.485	-0.143 ± 0.082	0.085
BBS Whitethroat	0.087 ± 0.002	<0.001	0.028 ± 0.002	<0.001	-0.017 ± 0.001	<0.001
LandSpAES Whitethroat	0.351 ± 0.111	0.002	0.060 ± 0.087	0.490	-0.092 ± 0.122	0.452
BBS Yellowhammer	0.054 ± 0.003	<0.001	0.126 ± 0.002	<0.001	-0.028 ± 0.002	<0.001
LandSpAES Yellowhammer	0.423 ± 0.155	0.008	0.067 ± 0.122	0.583	-0.105 ± 0.167	0.530

Table 5.1.4. Selected PCA axes for each bird species response variable

Response variable	PCA axes selected	
	LandSpAES	**BBS**
Lapwing Abundance	1, 2, 10, 11, 28	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28
Linnet Abundance	1, 2, 17, 20, 23	1, 2, 3, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28
Meadow Pipit Abundance	1, 2, 15, 21, 27	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28
Skylark Abundance	1, 2, 3, 12, 22	1, 2, 3, 5, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28
Whitethroat Abundance	1, 2, 17, 23, 27	1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28
Yellowhammer Abundance	1, 2, 7, 13, 15	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28

Table 5.1.5. Percentage of zero and non-zero counts in LandSpAES and BBS data for each species and the mean count observed across all years. Note that mean counts in LandSpAES were expected to be higher because there were more survey visits and longer lengths of survey transect.

	Scheme	% 0 Counts	% Non-0 Counts	Mean Count
Lapwing	BBS	79.01	20.99	1.23
	LandSpAES	74.55	25.45	3.35
Linnet	BBS	48.23	51.77	2.83
	LandSpAES	24.22	75.78	7.24
Meadow Pipit	BBS	83.23	16.77	1.39
	LandSpAES	61.72	38.28	9.87
Skylark	BBS	31.91	68.09	4.58
	LandSpAES	10.94	89.06	14.55
Whitethroat	BBS	30.47	69.53	2.7
	LandSpAES	17.27	82.73	6.59
Yellowhammer	BBS	39.47	60.53	2.58
	LandSpAES	23.64	76.36	5.79

There were large differences between the analogous parameter estimates from the LandSpAES and BBS models for many species (Table 5.1.3). For Lapwing and Meadow Pipit the proportions of LandSpAES squares with non-zero counts were very low (Table 5.1.5) and the uncertainty in some model estimates was very high (Table 5.1.3). Due to the large number of zeroes observed it was not possible to model abundance for these species in a robust way using the integrated modelling framework developed in the project. Therefore, we do not present figures for Lapwing or Meadow Pipit and do not consider the species for integrated modelling.

5.1.3.7.1 Lapwing abundance

Lapwing abundance showed contrasting relationships with both local and landscape AES gradients between BBS and LandSpAES. There was no relationship between LandSpAES Lapwing count and the AES gradients (all P-values >0.9). In BBS, however, the relationship at the 1km gradient scale was positive and at the 3km scale negative, and both relationships for BBS were highly significant (Table 5.1.3). As highlighted above, there was insufficient precision in the LandSpAES estimates due to sparsity of counts, and we do not proceed with modelling Lapwing abundance further.

5.1.3.7.2 Linnet abundance

After exploring the abundance of Linnets in LandSpAES and BBS survey data, we saw no similarity in the relationships across datasets. Figures 5.1.13 and 5.1.14 show these contrasting relationships, and we can see the significance of both local and landscape AES scores, and their interaction, in Table 5.1.3. In particular, we saw that for low and medium landscape (3km) AES scores, effects on Linnet abundance were very strongly positive, however for high 3km AES gradients, the predicted effect was negative (Figure 5.1.14).

Due to the differences in results between datasets for Linnet abundance, this will not be taken forward for integrated modelling.

Figure 5.1.13. Predicted relationships between Linnet abundance and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

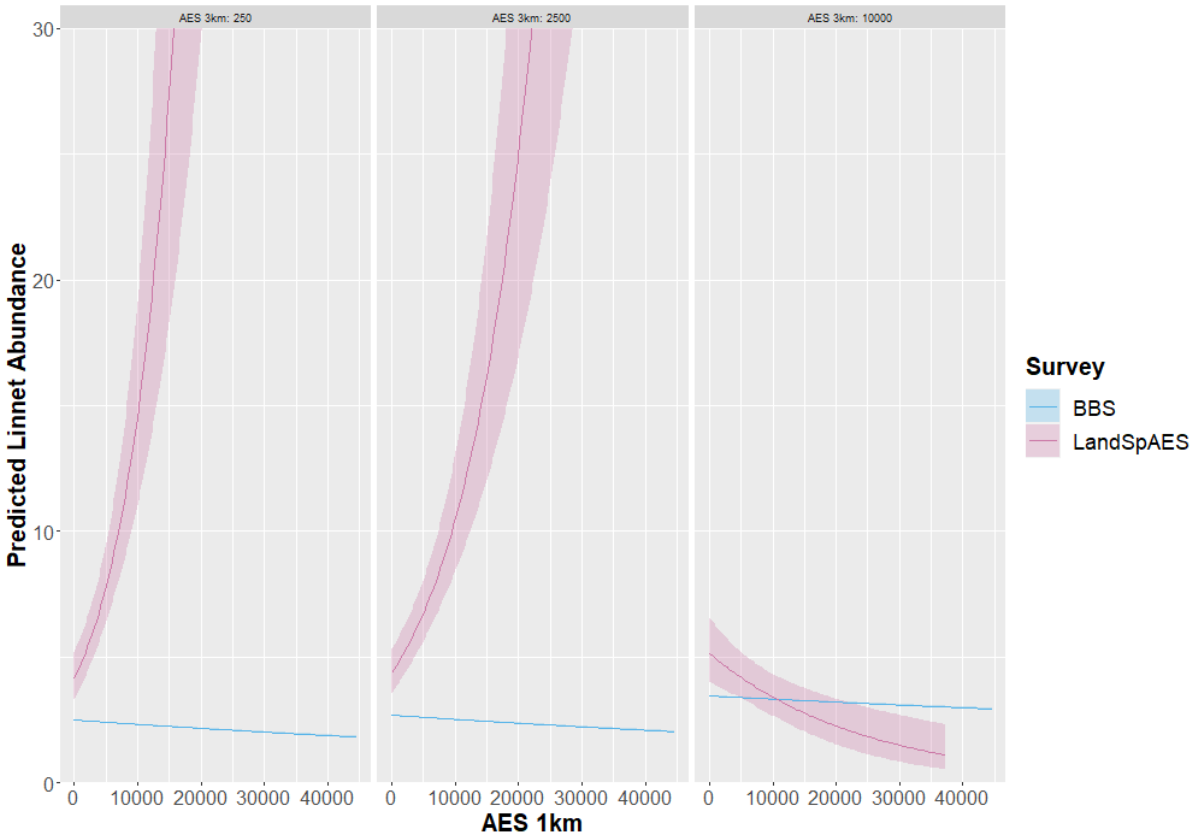

Figure 5.1.14. Predicted relationship between Linnet abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.3.7.3 Meadow Pipit abundance

At the 1km local scale, the relationship between Meadow Pipit abundance and AES gradient was positive and significant in both the LandSpAES and BBS datasets. There was a non-significant negative association at the 3km scale for LandSpAES data, and a significant negative relationship for BBS (Table 5.1.3). Despite these similar relationships shown in model estimates, the proportion of non-zero observations in LandSpAES was very low (Table 5.1.5) and therefore there was high uncertainty in LandSpAES results, indicating that combining datasets would not be valuable under the current modelling framework.

5.1.3.7.4 Skylark abundance

The relationship between Skylark abundance and local AES gradient contrasted between the LandSpAES and BBS datasets. For LandSpAES, we had a significant positive relationship, whilst in BBS the relationship was negative and significant. At the landscape scale, however, both schemes showed a positive relationship with AES, but this association was only significant for BBS (Figure 5.1.15 and Table 5.1.3). The BBS scheme displayed a significant interaction term, and in BBS this was positive whilst in LandSpAES it was negative. Figure 5.1.16 shows that relationships in LandSpAES are more strongly positive at lower 3km AES gradients.

The differences in responses between the two schemes for Skylark abundance mean that it is not suitable for formulating an integrated model.

Figure 5.1.15. Predicted relationships between Skylark abundance and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

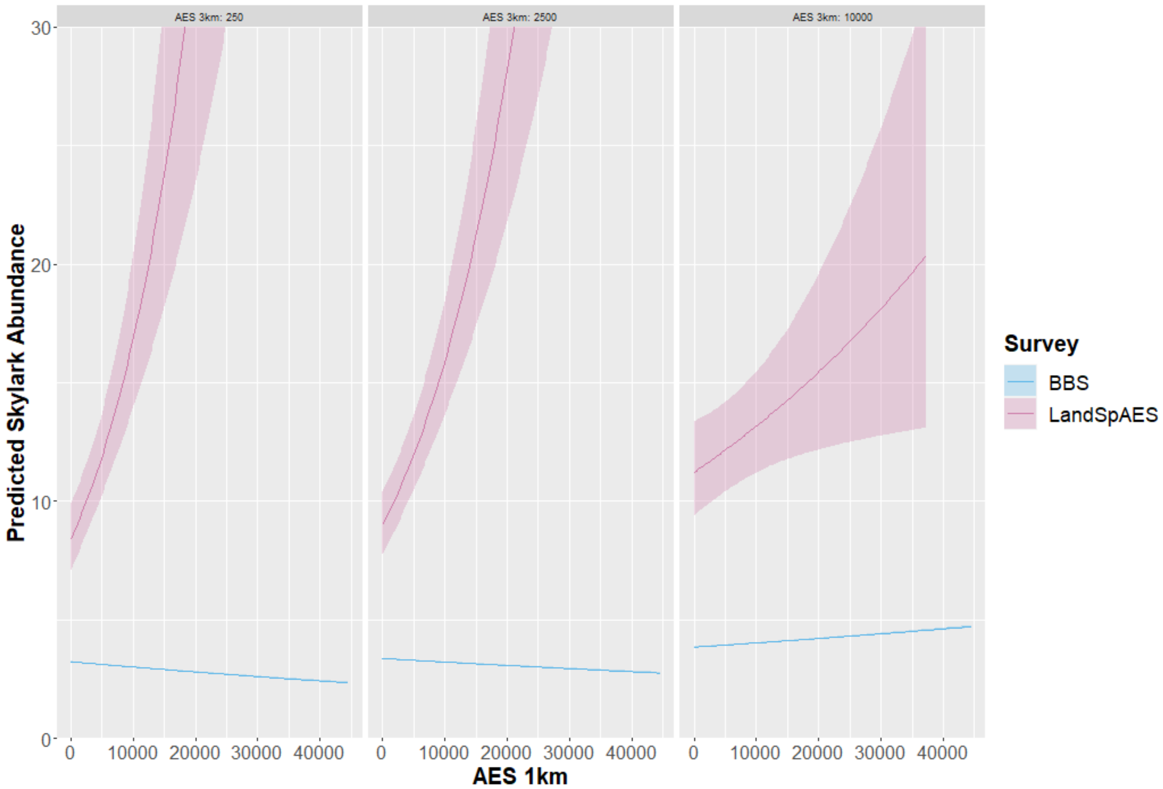

Figure 5.1.16. Predicted relationship between Skylark abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.3.7.5 Whitethroat abundance

For abundance of Whitethroat, there were similar relationships with both local and landscape AES gradients between LandSpAES and BBS. Both schemes showed a significant positive relationship with 1km AES, positive relationships with landscape AES and a negative interaction term (Figure 5.1.17 and Table 5.1.3). In BBS all associations were significant, whilst in LandSpAES, the only significant relationship occurred for local AES. In LandSpAES the interaction term indicated that the relationship between Whitethroat abundance and local (1km) AES was more strongly positive at lower levels of landscape (3km) AES (Figure 5.1.18).

Due to the similar relationships, we used Whitethroat abundance in the integrated modelling.

Figure 5.1.17. Predicted relationships between Whitethroat abundance and local (1km) and landscape (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

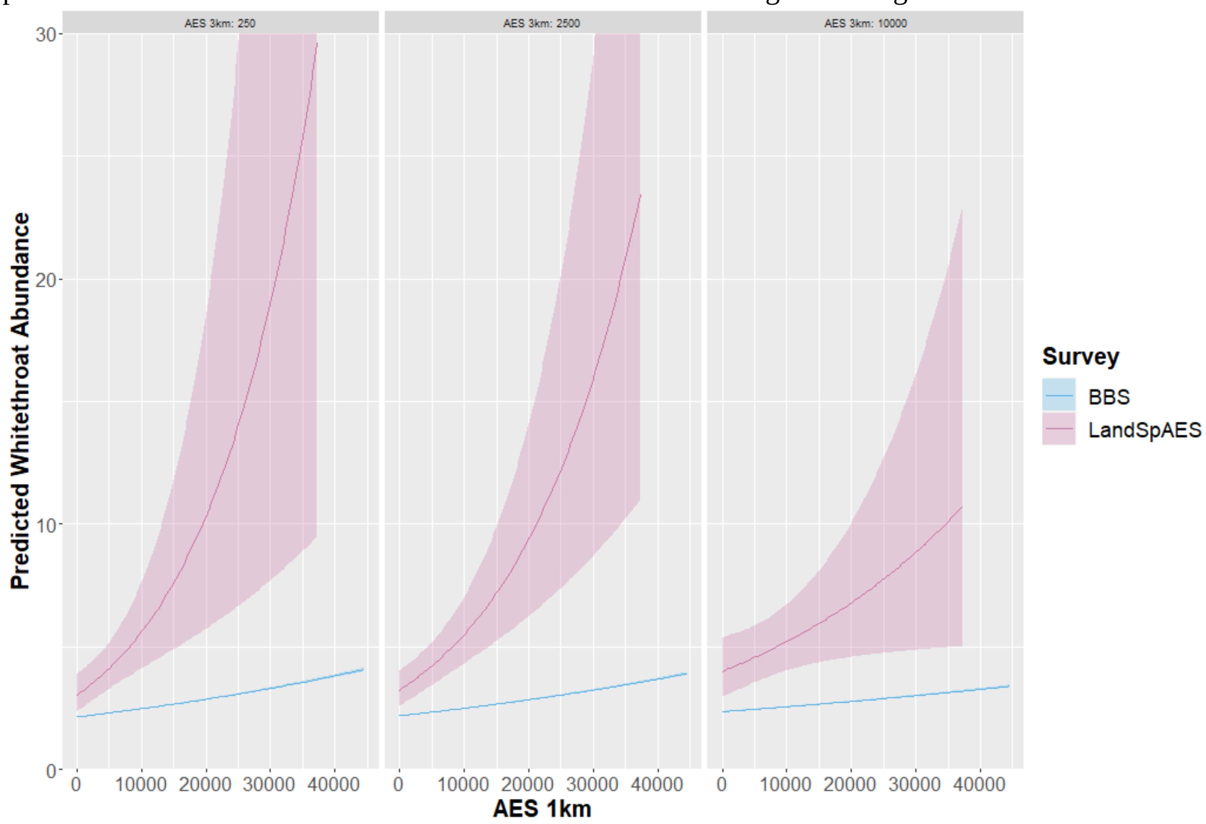

Figure 5.1.18. Predicted relationship between Whitethroat abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.3.7.6 Yellowhammer abundance

Yellowhammer abundance showed positive relationships with both local and landscape AES gradients in each of the BBS and LandSpAES schemes (Figure 5.1.19). At the local (1km) scale, both relationships in LandSpAES and BBS were positive and significant, whilst at the landscape (3km) level, both were positive but significant only for BBS. We had a significant negative interaction term in the BBS data, whilst in LandSpAES the association was negative, but non-significant (Table 5.1.3). In LandSpAES the interaction indicated that the relationship between Yellowhammer abundance and local (1km) AES was more strongly positive at lower levels of landscape (3km) AES (Figure 5.1.20).

The similarity in responses at both the local (1km) and landscape (3km) level mean that an integrated model of Yellowhammer abundance was considered suitable to explore.

Figure 5.1.19 Predicted relationships between Yellowhammer abundance and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

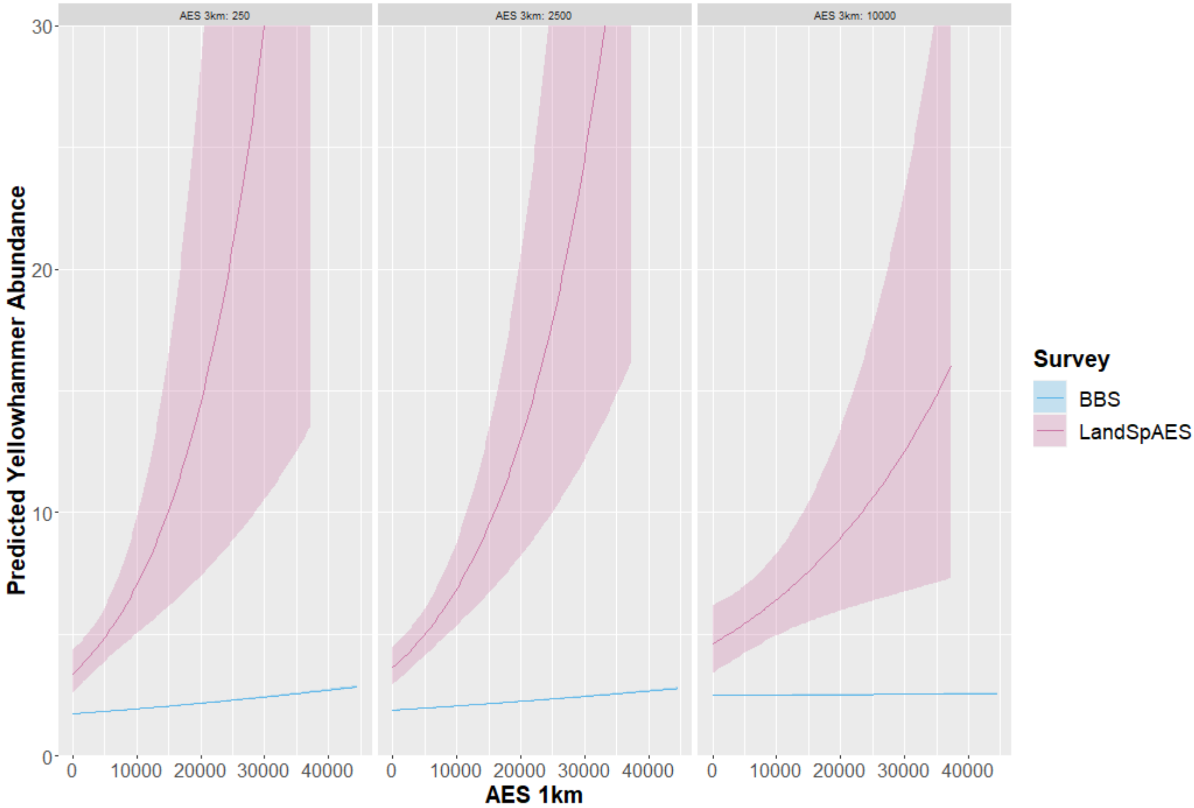

Figure 5.1.20. Predicted relationship between Yellowhammer abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BBS. Shaded areas indicate confidence intervals around the prediction.

5.1.4 Integrated models

Evidence from the individual scheme models indicated that the following responses would be suitable for integrated modelling:

- Whitethroat abundance
- Yellowhammer abundance

In order to compare integrated models with single species models, it was necessary to rescale the explanatory variables. Rescaling was performed for AES scores and PCA axes, and the results of this are reflected in the tables comparing estimated coefficients.

5.1.4.1 Whitethroat abundance

Using data from LandSpAES and BBS for individual scheme models, we found a positive response for Whitethroat abundance in relation to local (1km) AES gradient score and landscape (3km) score. To fit an integrated model for Whitethroat abundance, we combined both data sets and included all PCA axes selected in the original models, and a random term to account for the survey. We were not able to fit a random slope model to allow for differences in relationships with AES between datasets due to convergence warnings.

The integrated model showed the positive effect of AES gradients at the local and landscape scales (Figure 5.1.21), and these relationships were significant at both scales, as seen in the single dataset BBS model (Tables 5.1.3 and 5.1.6). The interaction term remains negative, but now significant, in line with the results seen previously for the model using BBS data. This shows that the integrated model is dominated by the BBS data, however plots now show wider confidence intervals for the integrated model than previously observed in the plots of BBS data models.

Table 5.1.6. Estimated relationships between Whitethroat abundance and AES gradients for LandSpAES and the integrated model, where AES gradient scores and PCA axis scores were rescaled in model fitting. Estimated coefficients are shown ± standard error.

Model	Local (1km)	P	Landscape (3km)	P	Interaction	P
LandSpAES	2.356 ± 0.655	<0.001	0.578 ± 0.381	0.129	-2.918 ± 2.232	0.191
Integrated	0.651 ± 0.010	<0.001	0.354 ± 0.014	<0.001	-1.049 ± 0.044	<0.001

If the integrated model of Whitethroat abundance reduced uncertainty in comparison to single data set models, we would see a reduction in root mean square error, the coefficient of variation and the median absolute error. Results for these tests are shown in Table 5.1.7, where we can see that the root mean squared error and the median absolute error was lower for the integrated model, and the coefficient of variation was smaller for the LandSpAES model. This highlights that the integrated model performs better than the LandSpAES model. The precision of estimation of the AES effects was much higher in the integrated model, shown by smaller standard errors in Table 5.1.6, emphasising again the increased confidence in the integrated model.

Table 5.1.7. Evaluation of integrated and LandSpAES models for Whitethroat abundance. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	RMSE	CV	MAE
LandSpAES	6.996	1.077	4.041
Integrated	3.506	1.299	1.232

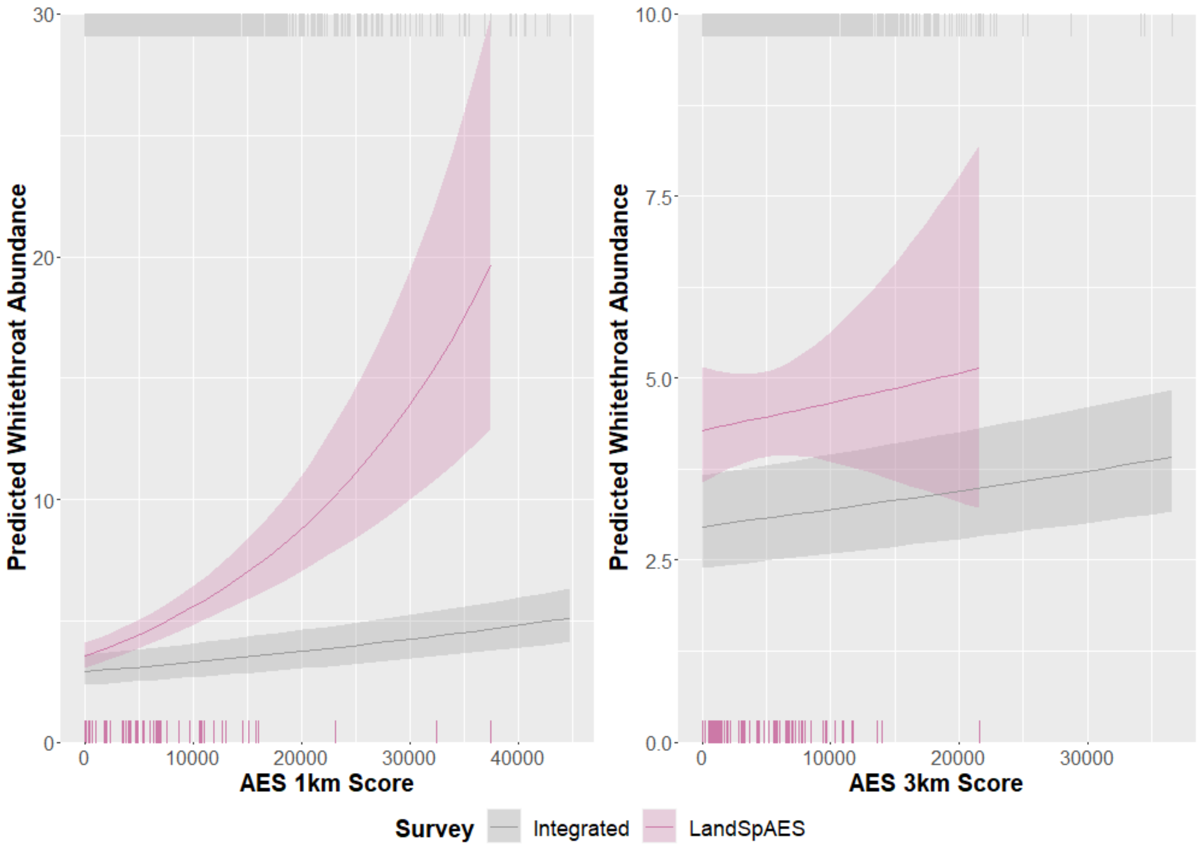

Figure 5.1.21. Comparison of predictions of Whitethroat abundance in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES model and an integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

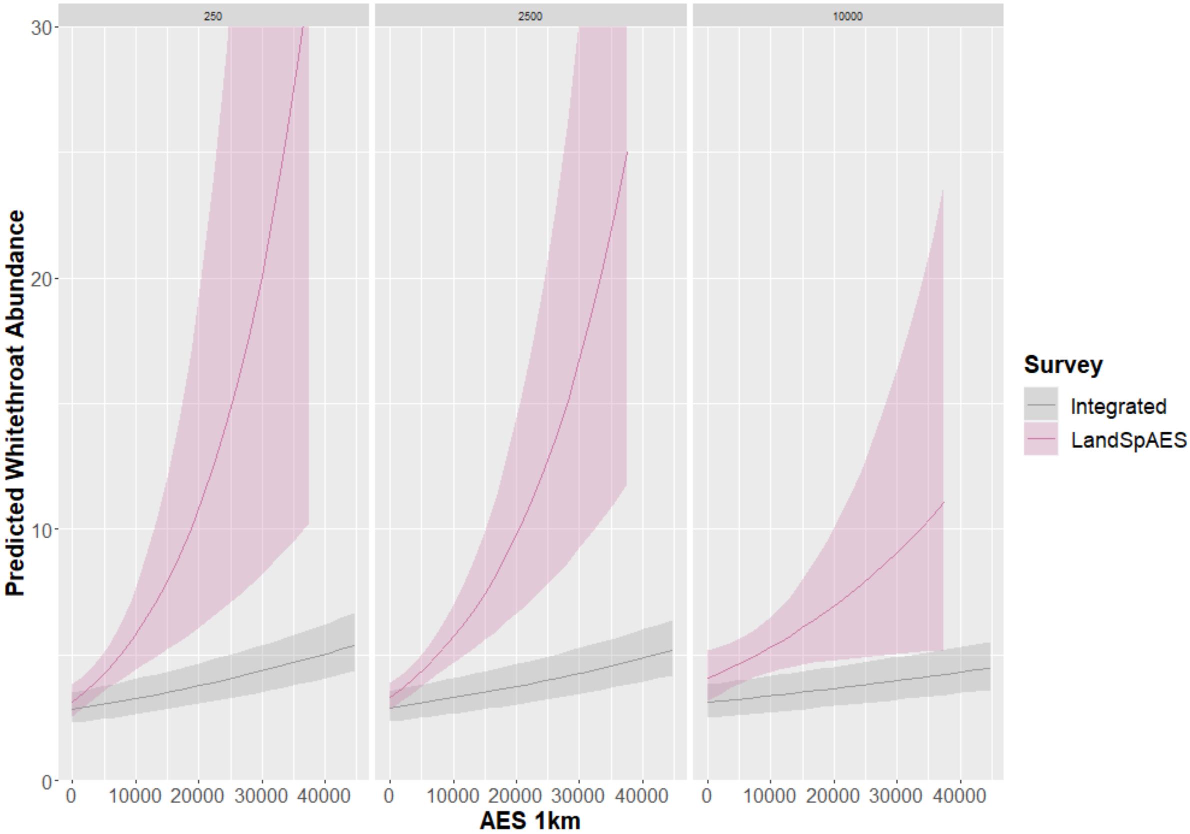

Figure 5.1.22. Predicted relationship between Whitethroat abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES and integrated model. Shaded areas indicate confidence intervals around the prediction.

5.1.4.2 Yellowhammer abundance

We used data from the LandSpAES and BBS schemes to fit an integrated model for Yellowhammer abundance. To account for any differences in habitat composition, we included all PCA axes selected for either the LandSpAES or BBS datasets (Table 5.1.1). In addition, we included a term to account for which survey scheme the data has been taken from. Due to model convergence warnings, we were not able to fit a random slope model to allow for differences in relationships with AES between schemes.

The integrated model showed the positive effect of AES gradients at both the local (1km) and landscape (3km) scale (Figure 5.1.23, 5.1.24). For the integrated model, there were significant relationships at the 1km and 3km scales (Table 5.1.8), matching the results found from the individual dataset BBS model. The interaction term remains negative and is significant in the integrated model. This highlights the integrated model is dominated by the BBS data; however, the plots show wider confidence intervals for the integrated model than previously observed in the plots of BBS data models.

Table 5.1.8. Estimated relationships between Yellowhammer abundance and AES gradients for LandSpAES and the integrated model, where AES gradient scores and PCA axis scores were rescaled in model fitting. Estimated coefficients are shown ± standard error.

Model	Local (1km)	P	Landscape (3km)	P	Interaction	P
LandSpAES	2.795 ± 0.768	<0.001	0.643 ± 0.435	0.140	-3.309 ± 2.534	0.192
Integrated	0.511 ± 0.011	<0.001	1.369 ± 0.014	<0.001	-1.790 ± 0.048	<0.001

To determine whether the integrated model of Yellowhammer abundance provided a reduction in uncertainty compared to single dataset models, we calculated the root mean square error, the coefficient of variation and the median absolute error. In Table 5.1.9, we can see that, again, the integrated model provides a lower uncertainty in results, with the RMSE and MAE being smaller than for the LandSpAES model. Additionally, the precision of estimation of the AES effects was higher in the integrated model, shown by smaller standard errors in Table 5.1.8. Hence, the integrated model provides a better prediction for Yellowhammer abundance.

Table 5.1.9. Evaluation of integrated and LandSpAES models for Yellowhammer abundance. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	RMSE	CV	MAE
LandSpAES	7.762	1.196	3.358
Integrated	3.643	1.410	1.121

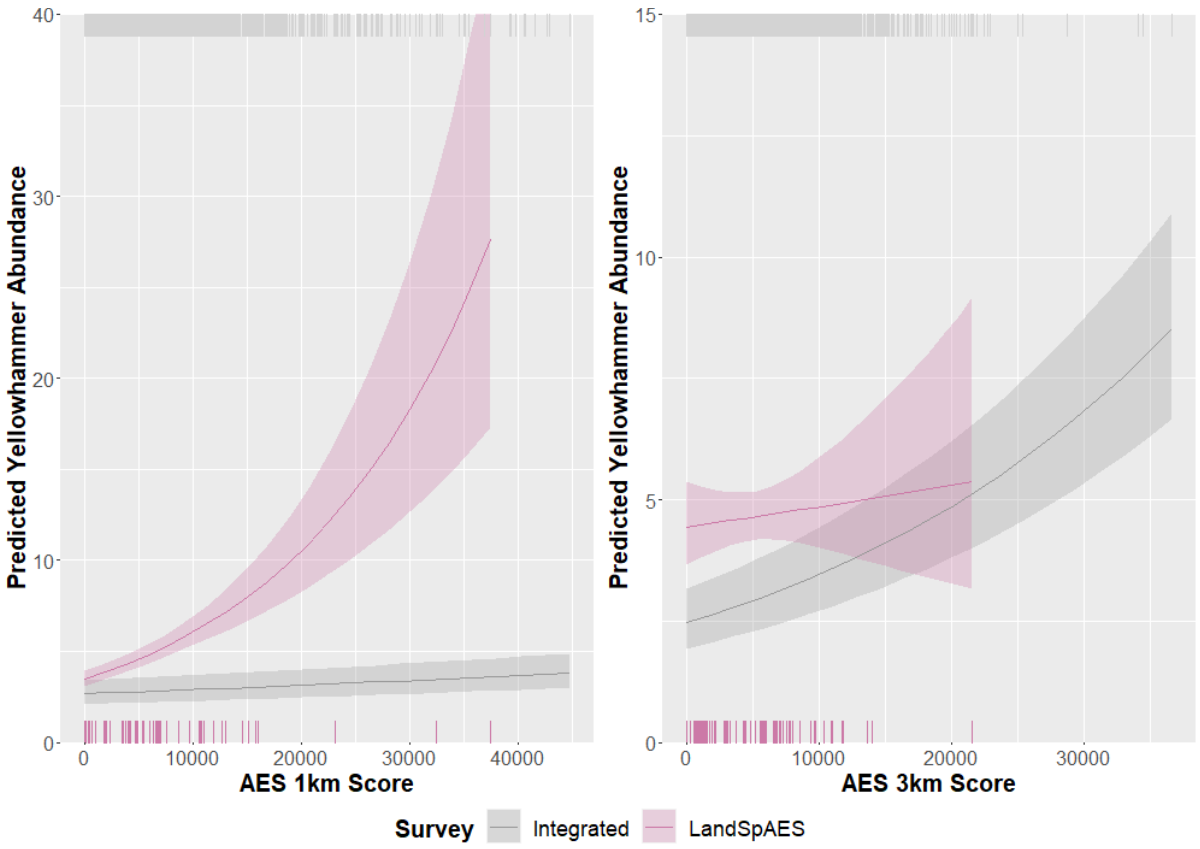

Figure 5.1.23. Comparison of predictions of Yellowhammer abundance in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES model and an integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

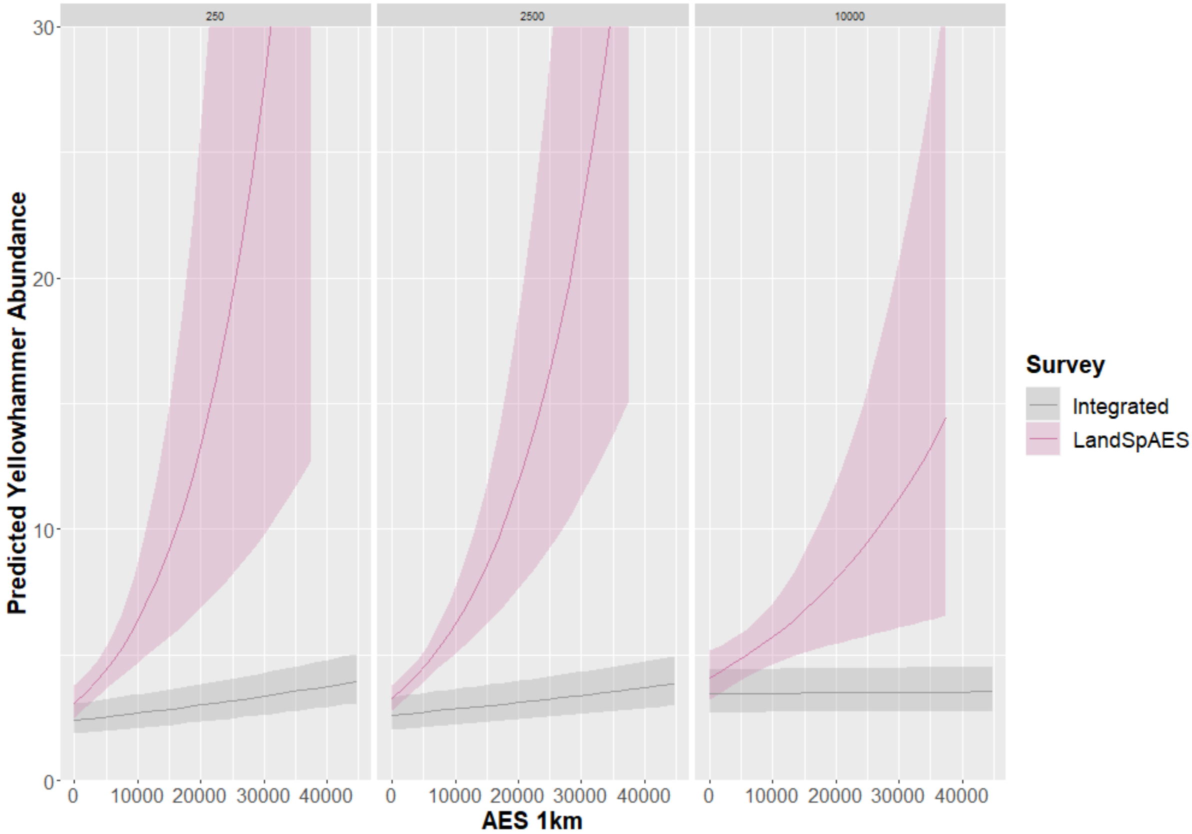

Figure 5.1.24. Predicted relationship between Yellowhammer abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES and integrated model. Shaded areas indicate confidence intervals around the prediction.

5.1.5. Discussion of bird results

There was little evidence of compelling associations between LandSpAES and BBS data sets for any of the assemblage-level bird responses (total abundance, richness, diversity, FBI abundance, FBI richness and Red List abundance). Where some relationships with AES gradients in the LandSpAES dataset were positive and significant (e.g. total abundance), the corresponding relationships in BBS data were either negative and significant, or non-significant. The same was true in some cases for the converse, where a relationship between AES gradient score and response could be positive in the BBS model (e.g. FBI species richness), but negative in the LandSpAES data. For all of these assemblage level responses, the interaction term differed in direction between LandSpAES and BBS, where in BBS the interaction term was always positive, and in LandSpAES always negative. For the responses calculated for the full species sets (total abundance, richness and diversity), these interaction terms are all significant for LandSpAES and non-significant for BBS. This could be in part due to the much higher sample size of the BBS and the survey design, where BBS is designed to explore abundance at large scales over an extended period, whilst LandSpAES used a higher intensity survey approach designed to separate local and landscape AES effects.

For the six exemplar farmland species (Lapwing, Linnet, Meadow Pipit, Skylark, Whitethroat and Yellowhammer) there were more similarities in the abundance responses between LandSpAES and BBS models. We anticipate individual species to respond more predictably than composite assemblage variables to AES management options across the country, so similarities for some species were to be expected. However, individual species may not all occur in all NCAs, and the removal of NCAs where a species does not occur results in smaller datasets for individual species than for the composite responses. This especially affects the smaller LandSpAES dataset.

In general, at the 3km scale, relationships between species abundance and AES gradient were more likely to be significant in BBS models. There was greater coverage of the AES gradients in the BBS data, highlighted by the rug points on plots shown in section 5.1.2, hence this increased chance of significance would be predicted, in the absence of other influences, such as survey method and background habitat effects. Due to the small sample sizes from LandSpAES data there were wide confidence intervals in prediction plots (Figures 5.1.13 – 5.1.20) for the single species models. Such confidence intervals would therefore also be expected for the less widespread species (Lapwing and Meadow Pipit), where data were more sparse, and were more likely to be zero-inflated, leading to poorer model fits. Integrated models combining data from multiple survey schemes could therefore provide greater power and more confidence in predictions.

For Lapwing and Meadow Pipit, the large proportion of squares where zeroes were observed made integrated models intractable under the current modelling framework. The inclusion of large numbers of PCA axes as predictors may also contribute to the dissimiliarity in relationships between the two datasets: some axes may have influenced presence/absence of the species and some variation in abundance, while the high BBS sample size provides power to support their inclusion. Further analyses could improve on this by considering zero-inflated models for this form of data, in which influences on the probability of counts being zero or non-zero and on the variability among non-zero counts are essentially modelled separately in a single framework. We avoided this approach here because adding zero inflation adds a huge degree of complexity to the integrated modelling and was out of scope in the time frame of this project. The need for these different approaches underlines a difficulty in applying common analytical approaches to generalise from analyses of one data set to another.

Whitethroat and Yellowhammer abundances were the only responses with sufficient similarity and model reliability to warrant integration of data for a further model. In each of these integrated models, uncertainties in the model estimates were reduced when compared against the models using only LandSpAES data. This was a result of the power of the BBS data in the integrated models, where we particularly saw the reduction of uncertainty at higher ends of the AES gradients. As mentioned previously, the BBS survey covers a wider range of AES options, but most critically has a sample size that is two orders of magnitude larger, thus leading to smaller confidence intervals and errors as AES increases, both at the 1km and 3km scales. The sample size difference means that integrated models effectively just reflected the results seen in the single BBS dataset models. We have tried to account for the important differences between the source data sets in the models, but it may be unlikely that datasets that vary so much in size, geographical coverage and proportion of zeroes can lead to consistent results, especially for species-level data, where detailed ecological dependencies may be more significant than they are for multi-species composite metrics. While species may be likely to respond more consistently to environmental predictors than composites responses, they are also more likely to be influenced by variations in sampling approach or landscape composition.

Overall, responses in BBS and LandSpAES often showed contrasting relationships. At the local (1km) scale, relationships between responses and AES were always positive in LandSpAES (except for Lapwing), though not always significant, but responses in BBS varied. The LandSpAES results reflect those found in interim analyses for that project and are yet to be explored in full, but may be related to the positive effects of an accumulation of AES effects in areas where ongoing Environmental and Countryside Stewardship agreements have built upon those from previous schemes. The same influences would be expected to affect metrics from BBS data, although their detection may be compromised by the sparsity of high-AES data.

Integrated models were fitted for responses that showed similarities between LandSpAES and BBS results in the initial modelling stages and these showed reduced uncertainty in model estimates for the responses explored. There will always be more uncertainty in analyses for individual species, because of the greater heterogeneity in counts, relative to assemblage-level, combined data, but individual species will also always be more sensitive to variation in environmental predictors; the results suggest that integrated modelling will be more tractable at the species level for birds, as a result. However, this is still only true for one third of the species considered and the general conclusion for birds must be that integrated modelling does not appear to be helpful to evaluate AES effects.

5.2 Butterflies

Butterflies are recorded by two CitSci schemes, the Wider Countryside Butterfly Survey (WCBS) and the UK Butterfly Monitoring Scheme (UKBMS). We have considered these schemes separately due to slight differences in protocols and design between the two CitSci surveys. For example, the WCBS was designed to avoid potential bias towards species rich habitats that could arise from free placement of transects.

For these reasons we might expect different relationships between butterfly responses and AES in these CitSci schemes and will keep them separate throughout.

5.2.1. Accounting for protocol differences

There are several differences in design and protocols between the three butterfly datasets, as detailed in the scoping (Sections 3.2.2. and 3.2.3).

5.2.1.1. Survey unit and transect placement

The survey units differ between the two CitSci butterfly schemes, with WCBS transects being restricted to a focal 1km square (like the LandSpAES survey squares), whereas UKBMS transects can extend beyond a 1km square (see Section 3.2).

UKBMS has variable transect lengths, whereas transect length in LandSpAES and WCBS is fixed at approximately 2 km. We did not account for variable transect lengths in UKBMS within the modelling as it is not currently available for all transects.

5.2.1.2. Number of visits

UKBMS has weekly visits between April and September. WCBS has a minimum of two visits in July and August, but some squares have more visits than this. For both volunteer led schemes there is the potential for missing visits. We accounted for variation in number of visits within and between schemes by including a fixed effect for number of visits. For both CitSci schemes, we subset the data to include only visits in May to August to match the LandSpAES survey window.

5.2.1.3. Taxonomic identification differences

Small and Essex skipper butterflies were sometimes recorded as separate species and sometimes as an aggregate in all surveys. In LandSpAES, aggregate records were few, and were allocated to species based on proportions of the two species observed in the square or NCA. It was not feasible to do this for UKBMS and WCBS, so all records of these species were aggregated to Small/Essex skipper to avoid overestimating species richness in squares where both the aggregate and single species were recorded.

5.2.2. Explaining NCA variation

Using the PCA axes approach described in Section 4.3.2 we identified a number of axes which explained variation previously attributed to NCA for each response. Replacing NCA random effect with PCA axes had a minor impact interpretation of the LandSpAES models. For butterfly diversity and abundance, local level AES effects which were non-significant ($0.05 < P < 0.1$) in the original LandSpAES models (with NCA random effect) became significant ($P < 0.05$) when the NCA random effect was replaced with PCA axes (Appendix 1 Table A2). The gradient interaction term in the LandSpAES abundance model was also non-significant with the NCA random effect, but significantly negative with addition of PCA axes.

Table 5.2.1. Selected PCA axes for each response variable.

Response variable	PCA axes selected		
	LandSpAES	**WCBS**	**UKBMS**
Butterfly richness	1, 2	1, 2, 6, 15, 21, 23	1, 2, 6, 11, 21, 23
Butterfly diversity	1, 2, 13	1, 2, 3, 7, 13, 15	1, 2, 3, 7, 13, 21
Butterfly abundance	1, 2, 9	1, 2, 6, 15, 19, 20	1, 2, 6, 19, 21, 23

5.2.3. Results of individual scheme models

5.2.3.1 Butterfly species richness

All datasets showed a positive relationship with 1km AES, a positive relationship with landscape AES and a negative interaction term (Table 5.2.2; Figures 5.2.1, 5.2.2). In all datasets, the interaction term indicated that the relationship between species richness and local (1km) AES was more strongly positive at lower levels of landscape (3km) AES. In LandSpAES these relationships were not significant (matching the provisional results, see Section 1.3), but these relationships were highly significant in both WCBS and UKBMS, suggesting that lack of significance in LandSpAES may be a function of small sample size.

On average, LandSpAES records slightly more species of butterfly per year when standardized by the number of surveys.

Table 5.2.2. Estimated relationships between butterfly richness and AES gradients for LandSpAES, UKBMS and WCBS. Estimated coefficients are shown ± standard error.

Survey	**Local (1km)**	***P***	**Landscape (3km)**	***P***	**Interaction**	***P***
LandSpAES	0.050 ± 0.041	0.229	0.032 ± 0.025	0.197	-0.029 ± 0.037	0.439
UKBMS	0.026 ± 0.004	<0.001	0.021 ± 0.004	<0.001	-0.008 ± 0.002	<0.001
WCBS	0.045 ± 0.012	<0.001	0.042 ± 0.008	<0.001	-0.021 ± 0.005	<0.001

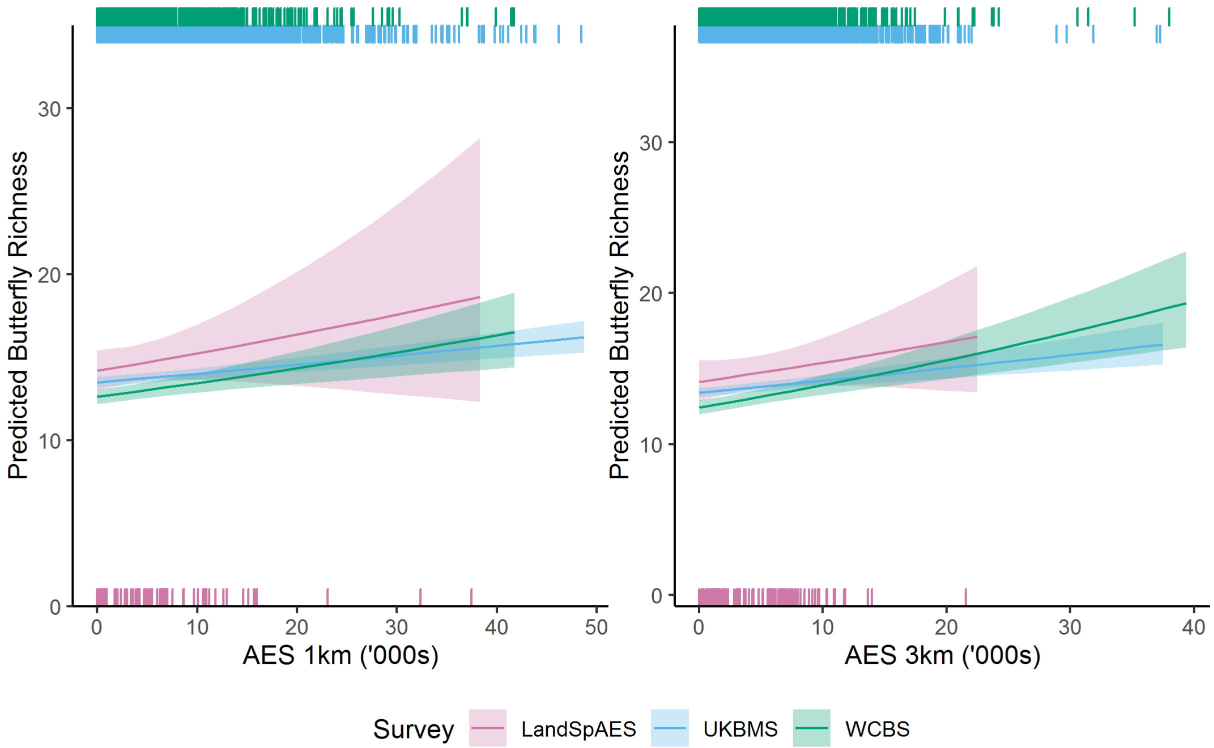

Figure 5.2.1. Predicted relationships between butterfly species richness and local level (1km) and landscape level (3km) AES gradients for LandSpAES, UKBMS and WCBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

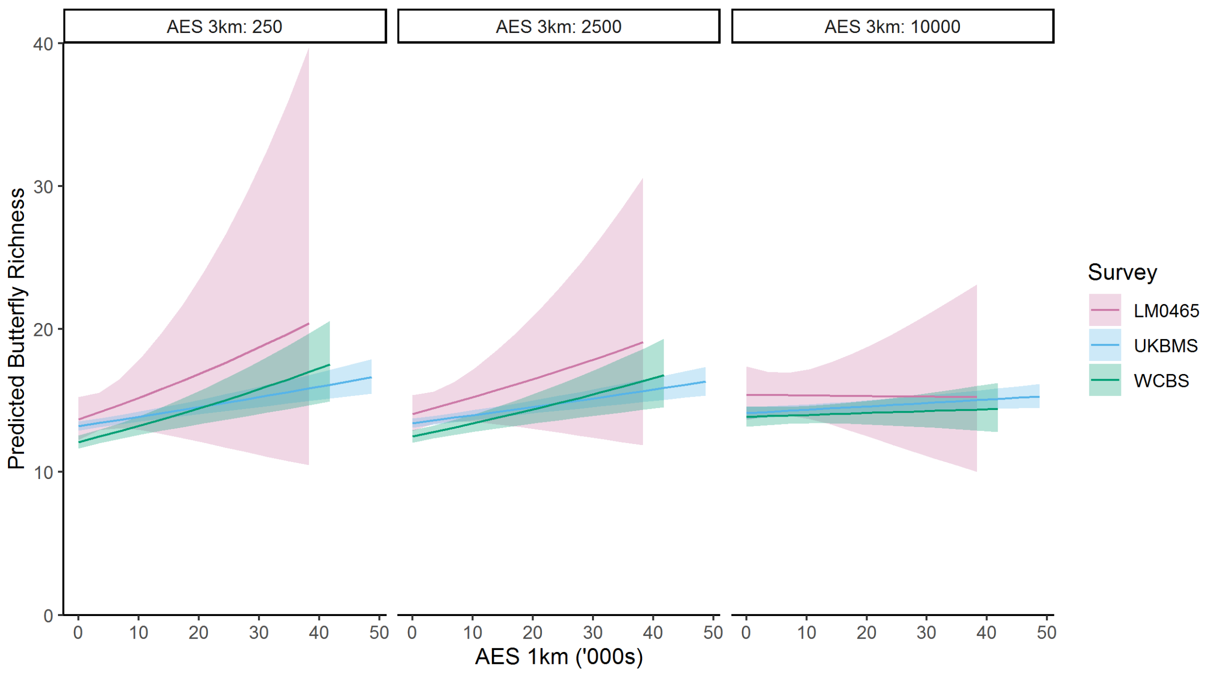

Figure 5.2.2. Predicted relationship between butterfly species richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES, UKBMS and WCBS. Shaded areas indicate confidence intervals around the prediction.

The z-test confirmed the similar relationships with both local and landscape AES gradients between LandSpAES, WCBS and UKBMS (Table 5.2.3). There were no significant differences between AES coefficients in LandSpAES and either butterfly scheme. However, there were some differences between estimated relationships with landscape (3km) AES and interaction effects between WCBS and UKBMS.

Table 5.2.3. Z-test results for comparisons of AES coefficients between LandSpAES, WCBS and UKBMS for butterfly species richness.

Comparison	1km AES	3km AES	Interaction
LandSpAES - WCBS	z = 0.115, *P* = 0.910	z = -0.391, *P* = 0.695	z = -0.201, *P* = 0.841
LandSpAES - UKBMS	z = 0.564, *P* = 0.572	z = 0.419, *P* = 0.675	z = -0.550, *P* = 0.582
WCBS - UKBMS	z = -1.476, *P* = 0.140	z = -2.167, *P* = 0.030	z = 2.385, *P* = 0.017

5.2.3.2. Butterfly diversity

For butterfly diversity we found somewhat dissimilar relationships with AES gradients between LandSpAES, WCBS and UKBMS (Table 5.2.4). LandSpAES data showed some evidence of a positive relationship with local level AES (coefficient = 0.646, s.e. of coefficient = 0.302, $P = 0.034$), whereas both WCBS and UKBMS datasets showed a positive relationship between butterfly diversity and landscape scale AES ($P < 0.01$ in both cases; Figures 5.2.3, 5.2.4).

Table 5.2.4. Estimated relationships between butterfly diversity (exponential transformed Shannon index) and AES gradients for LandSpAES, UKBMS and WCBS. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.646 ± 0.302	0.034	-0.146 ± 0.169	0.387	-0.377 ± 0.259	0.148
UKBMS	-0.06 ± 0.049	0.220	0.13 ± 0.05	0.009	0.006 ± 0.025	0.795
WCBS	0.029 ± 0.078	0.709	0.176 ± 0.056	0.002	-0.044 ± 0.031	0.161

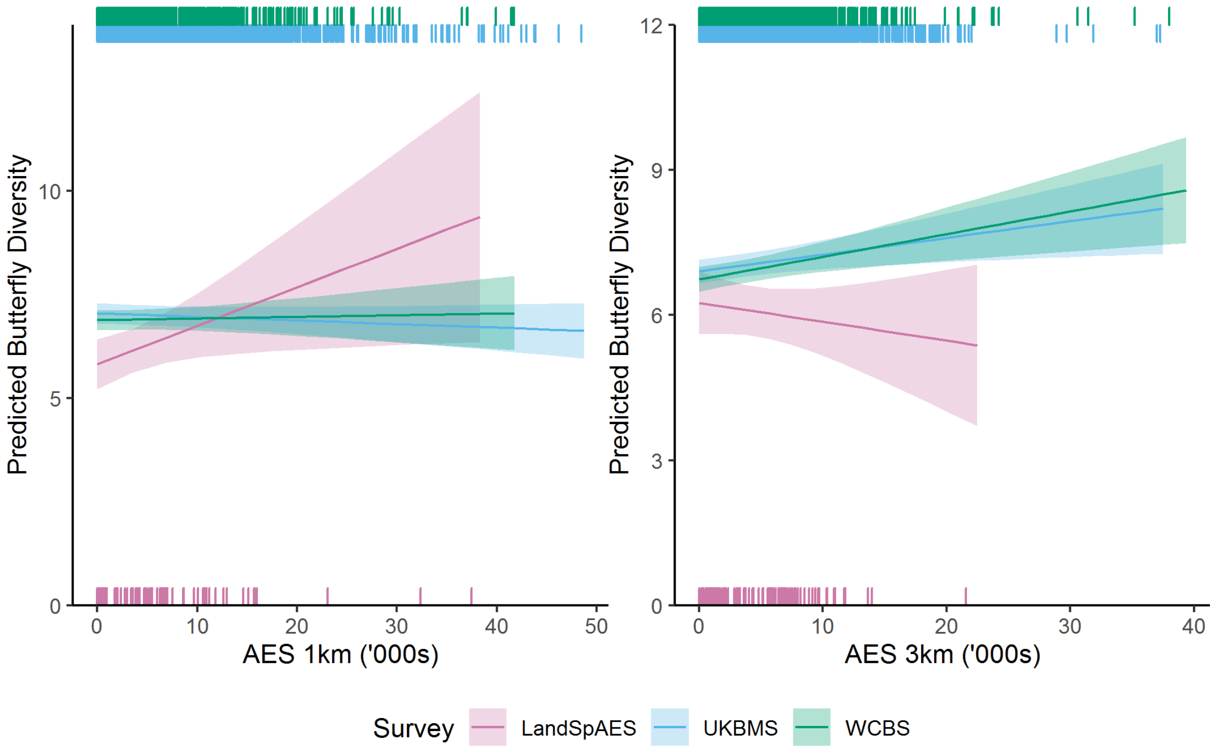

Figure 5.2.3. Predicted relationships between butterfly diversity (exponential transformed Shannon index) and local level (1km) and landscape level (3km) AES gradient for LandSpAES, UKBMS and WCBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

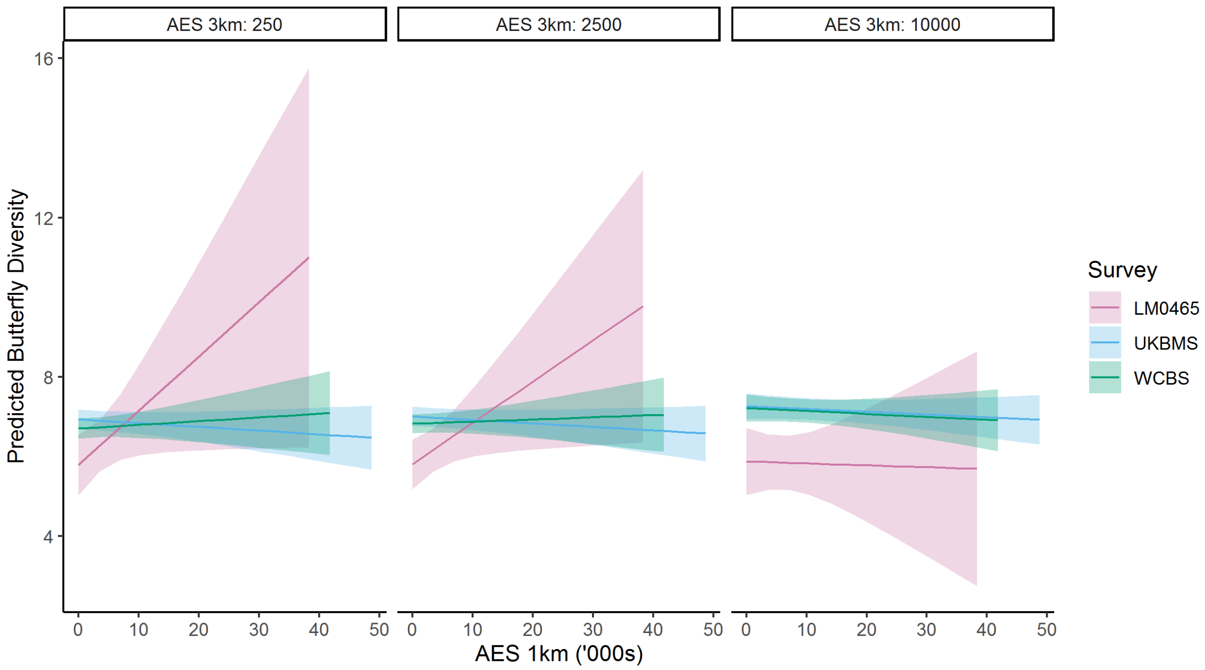

Figure 5.2.4. Predicted relationship between butterfly diversity (exponential transformed Shannon index) and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES, UKBMS and WCBS. Shaded areas indicate confidence intervals around the prediction.

Application of the z-test (Table 5.2.5) indicated slight evidence for a difference in local level AES terms between LandSpAES and WCBS (P = 0.047), with stronger evidence of a difference between LandSpAES and UKBMS (P = 0.021), likely due to lower uncertainty around coefficient estimates for UKBMS.

Table 5.2.5. Z-test results for comparisons of AES coefficients between LandSpAES, WCBS and UKBMS for butterfly diversity (exponential transformed Shannon index).

Comparison	1km AES	3km AES	Interaction
LandSpAES - WCBS	z = 1.980, P = 0.048	z = -1.811, P = 0.070	z = -0.276, P = 0.202
LandSpAES - UKBMS	z = 2.310, P = 0.021	z = -1.570, P = 0.116	z = -1.474, P = 0.116
WCBS - UKBMS	z = -0.971, P = 0.332	z = -0.611, P = 0.542	z = 1.258, P = 0.208

5.2.3.3. Butterfly abundance

Relationships between butterfly abundance and local and landscape AES gradients were broadly similar for all three butterfly datasets (Table 5.2.6; Figures 5.2.5, 5.2.6). All surveys showed positive relationships between butterfly abundance and local (1km) level AES (all significant at $P < 0.05$) and positive relationships between abundance and landscape (3km) level AES (all significant at $P < 0.01$). In addition, all surveys found some evidence of an interaction between local and landscape AES, with a stronger effect of local level AES observed at low landscape level AES.

Table 5.2.6. Estimated relationships between butterfly abundance and AES gradients for LandSpAES, UKBMS and WCBS. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.164 ± 0.078	0.035	0.178 ± 0.044	<0.001	-0.157 ± 0.068	0.021
UKBMS	0.084 ± 0.015	<0.001	0.041 ± 0.015	0.007	-0.015 ± 0.008	0.044
WCBS	0.155 ± 0.03	<0.001	0.109 ± 0.021	<0.001	-0.034 ± 0.012	0.004

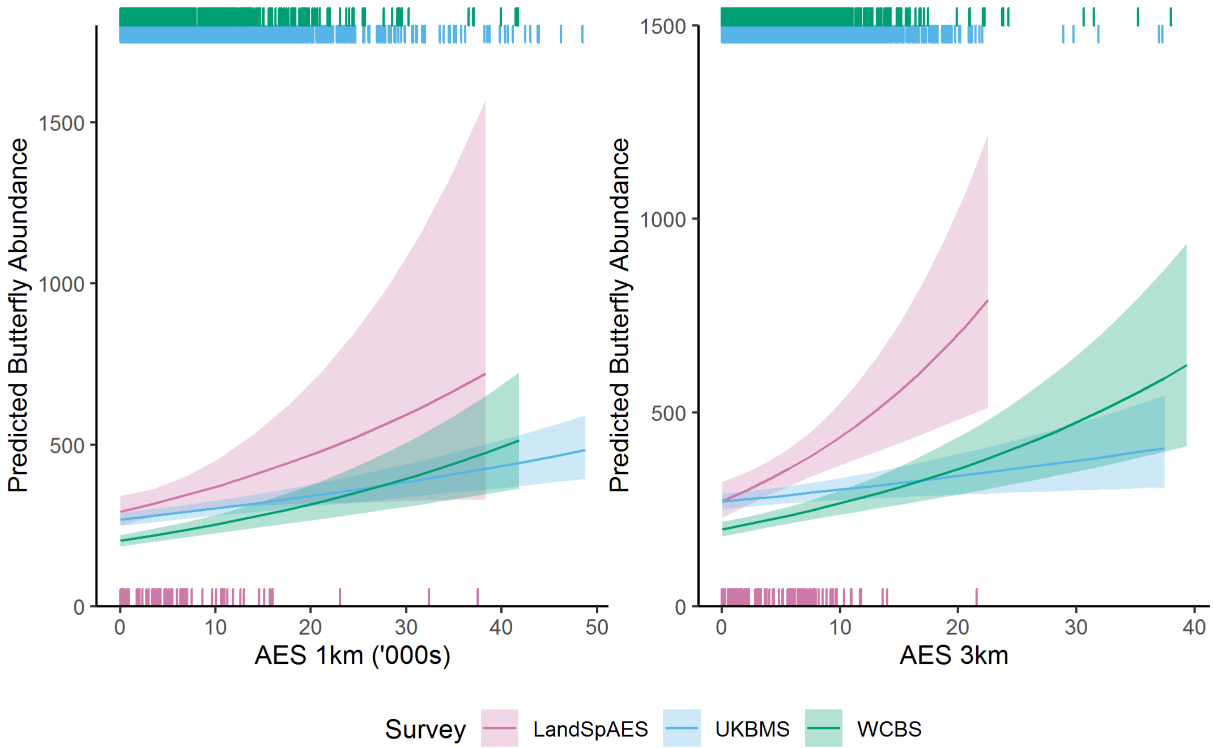

Figure 5.2.5. Predicted relationship between butterfly abundance and local level (1km) AES gradient for LandSpAES, UKBMS and WCBS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

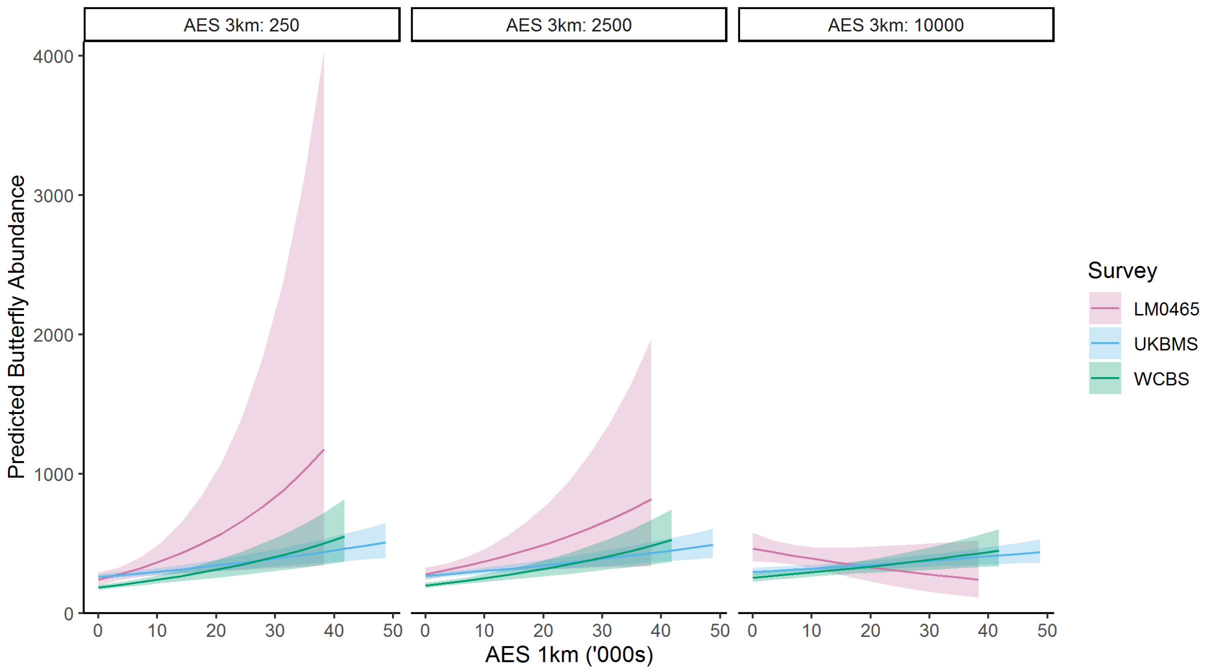

Figure 5.2.6. Predicted relationship between butterfly abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES, UKBMS and WCBS. Shaded areas indicate confidence intervals around the prediction.

Application of the z-test showed no significant differences in coefficients between LandSpAES and WCBS (Table 5.2.7) but a clear difference in the estimated relationship with landscape AES between LandSpAES and UKBMS with the estimated slope being much steeper in LandSpAES.

Table 5.2.7. Z-test results for comparisons of AES coefficients between LandSpAES, WCBS and UKBMS for butterfly abundance.

Comparison	1km AES	3km AES	Interaction
LandSpAES - WCBS	z = 0.106, *P* = 0.915	z = 1.430, *P* = 0.153	z = -1.793, *P* = 0.073
LandSpAES - UKBMS	z = 1.013, *P* = 0.311	z = 2.957, *P* = 0.003	z = -2.078, *P* = 0.038
WCBS - UKBMS	z = -2.156, *P* = 0.031	z = -2.584, *P* = 0.010	z = 1.315, *P* = 0.189

5.2.4. Integrated models

5.2.4.1. Butterfly species richness

Evidence from the individual survey models (Section 5.2.2.1) suggested that there was good support for fitting an integrated model to butterfly species richness, though the z tests showed there were some differences between the WCBS and UKBMS schemes. Firstly, we fitted an integrated model including all three schemes, with terms to account for between scheme differences in mean butterfly richness (e.g. due to survey design differences). We were not able to fit a random slope model to allow for differences in relationships with AES between schemes due to model convergence warnings.

The integrated model indicated a significant positive effect of both local and landscape AES (Table 5.2.8; Figures 5.2.7, 5.2.8). In both cases the integrated model showed relationships with AES that were similar to LandSpAES, but in the integrated model these were significant.

Table 5.2.8. Estimated relationships between butterfly richness and AES gradients for LandSpAES and the integrated model. Estimated coefficients are shown ± standard error.

Model	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.050 ± 0.041	0.229	0.032 ± 0.025	0.197	-0.029 ± 0.037	0.439
Integrated	0.026 ± 0.004	<0.001	0.025 ± 0.004	<0.001	-0.010 ± 0.002	<0.001

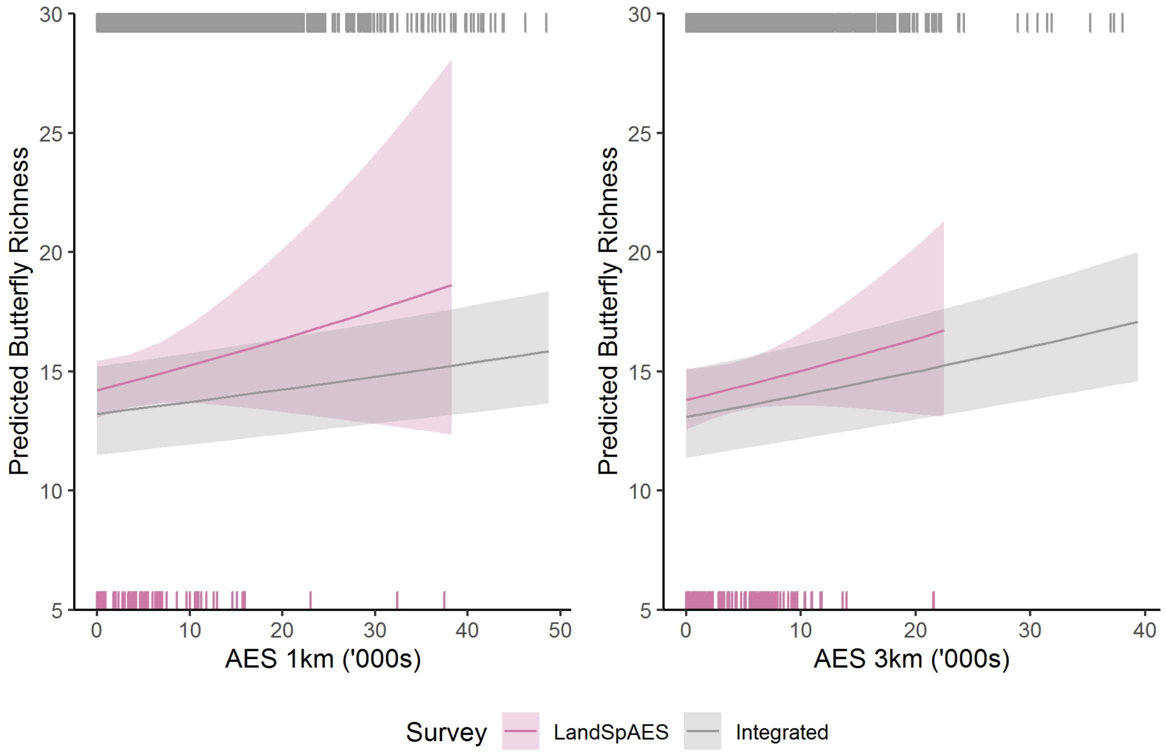

Figure 5.2.7. Comparison of predictions of butterfly richness in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES data and integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of data along the AES gradients.

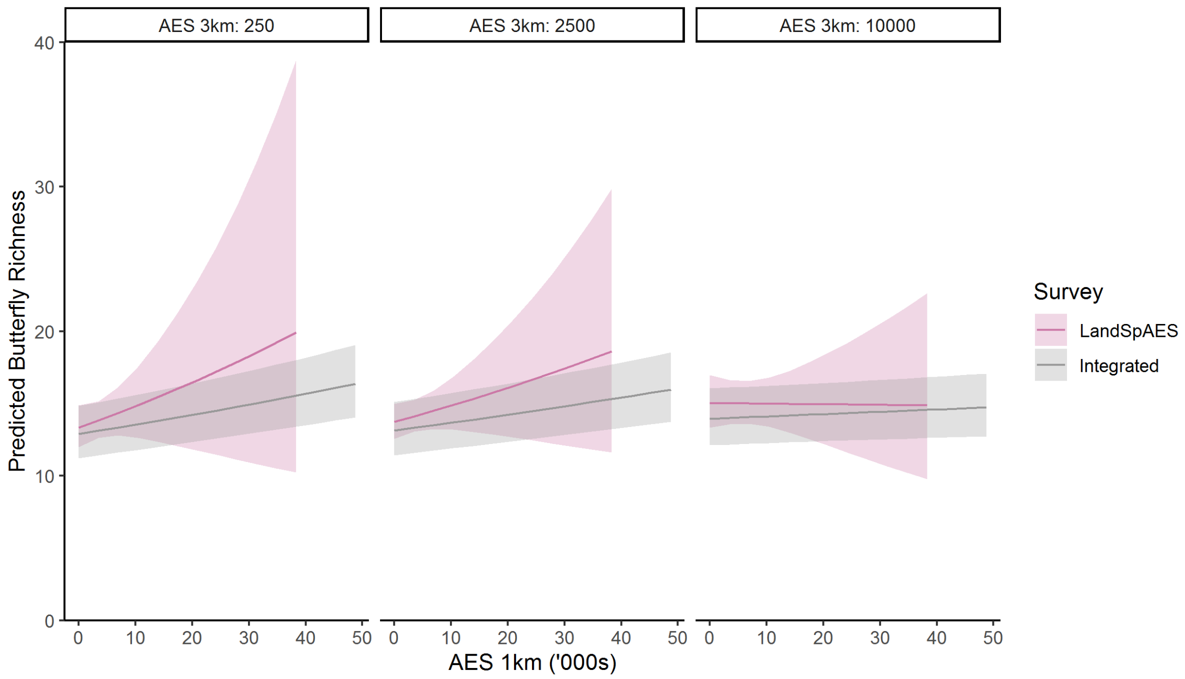

Figure 5.2.8. Predicted relationship between butterfly richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES model and integrated model. Shaded areas indicate confidence intervals around the prediction.

Evaluation of the integrated model for butterfly species richness suggested that uncertainty in the integrated model was higher than in the LandSpAES model, shown by higher MAE, RMSE and CV. However, precision of estimation of the AES effects was much higher in the integrated model, shown by smaller standard errors in Table 5.2.8.

Table 5.2.9. Evaluation of integrated and LandSpAES models. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	**MAE**	**RMSE**	**CV**
LandSpAES	12.970	13.047	0.863
Integrated	14.518	15.272	0.909

High uncertainty in this model may arise from inclusion of both WCBS and UKBMS datasets, as the z-test for species richness suggested a significant difference between the coefficients in each dataset. To test this, we also ran the butterfly richness integrated model with LandSpAES and WCBS only. We chose WCBS over UKBMS for this comparison as the similarity between LandSpAES and WCBS coefficients was higher according to the z-test results (lower z scores).

When only WCBS and LandSpAES were used to fit an integrated model we again found significant positive relationships between butterfly species richness and both AES gradients, plus a significant interaction term indicating a more positive relationship with local AES and low landscape AES (Table 5.2.10, Figures 5.2.9, 5.2.10).

Table 5.2.10. Estimated relationships between butterfly richness and AES gradients for LandSpAES and the integrated model when only WCBS was included. Estimated coefficients are shown ± standard error.

Model	**Local (1km)**	***P***	**Landscape (3km)**	***P***	**Interaction**	***P***
LandSpAES	0.050 ± 0.041	0.229	0.032 ± 0.025	0.197	-0.029 ± 0.037	0.439
Integrated	0.044 ± 0.01	<0.001	0.040 ± 0.008	<0.001	-0.019 ± 0.005	<0.001

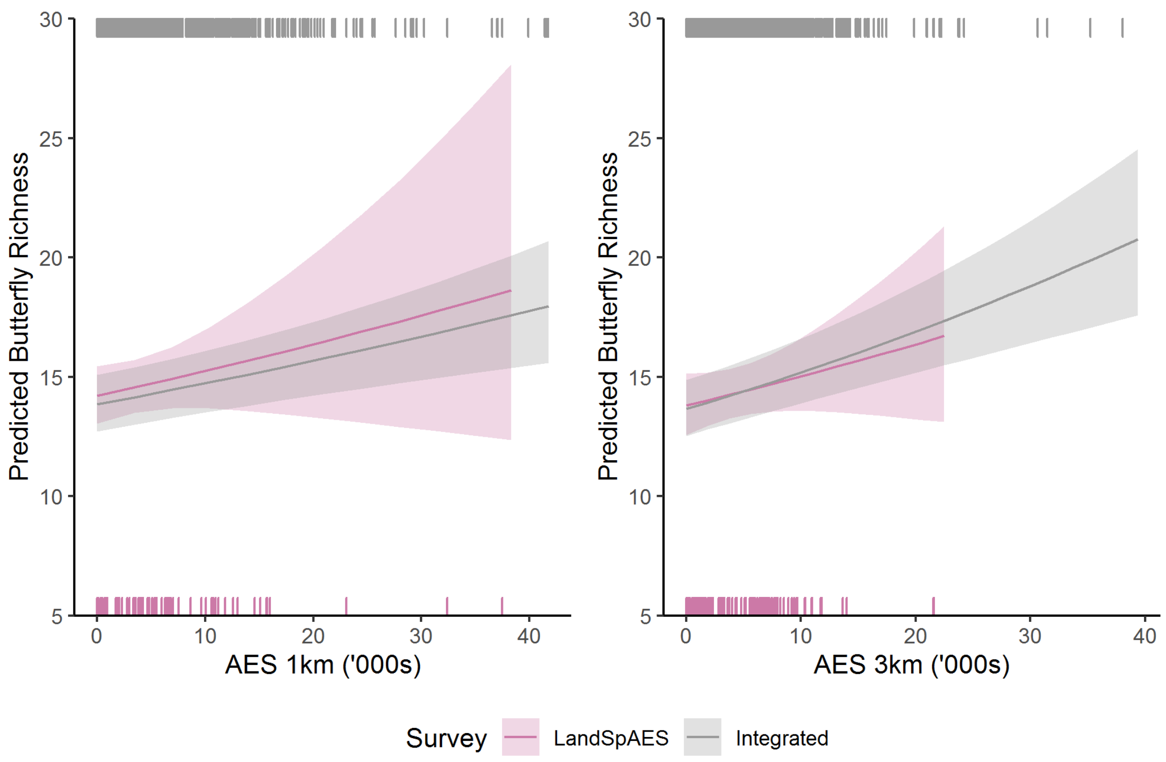

Figure 5.2.9. Comparison of predictions of butterfly richness in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES data and integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of data along the AES gradients.

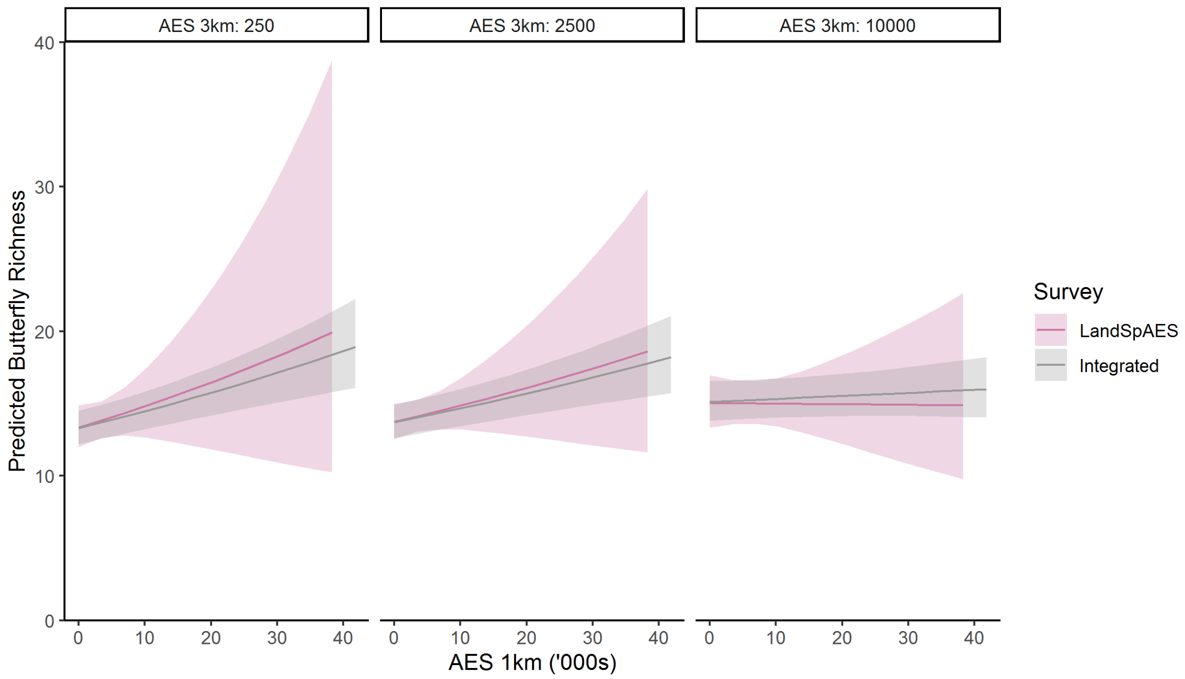

Figure 5.2.10. Predicted relationship between butterfly richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES model and integrated model. Shaded areas indicate confidence intervals around the prediction.

Evaluation of the integrated model with WCBS and LandSpAES showed that the integrated model had lower MAE and RMSE, and a comparable coefficient of variation (Table 5.2.11).

Table 5.2.11. Evaluation of integrated (WCBS only) and LandSpAES models. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	MAE	RMSE	CV
LandSpAES	12.970	13.047	0.863
Integrated	8.585	9.566	0.865

5.2.4.2. Butterfly diversity

Evidence from individual scheme models showed moderate support for fitting an integrated model, with some differences observed between LandSpAES and the CitSci datasets. To account for this lower level of support for shared relationships with AES we fit a model that allowed relationships with AES to vary between schemes, as well as allowing schemes to have different mean responses. Because we were able to use a normal distribution to model butterfly diversity (after transformation) we were able to fit this more complicated model without any model performance issues.

The integrated model showed no significant relationships with either local or landscape level AES, and no significant interaction term (Table 5.2.12). This contrasts with the results of the individual scheme models where the LandSpAES model showed a positive effect of local level (1km) AES whilst WCBS and UKBMS showed a positive effect of landscape level (3km) AES. Plotting the estimated relationships shows that the integrated model has equal or higher uncertainty than the LandSpAES model (Figures 5.2.11, 5.2.12).

Table 5.2.12. Estimated relationships between butterfly diversity (exponential transformed Shannon index) and AES gradients for LandSpAES and the integrated model. Estimated coefficients are shown ± standard error.

Model	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.646 ± 0.302	0.034	-0.146 ± 0.169	0.387	-0.377 ± 0.259	0.148
Integrated	0.218 ± 0.272	0.422	-0.217 ± 0.294	0.665	-0.115 ± 0.105	0.271

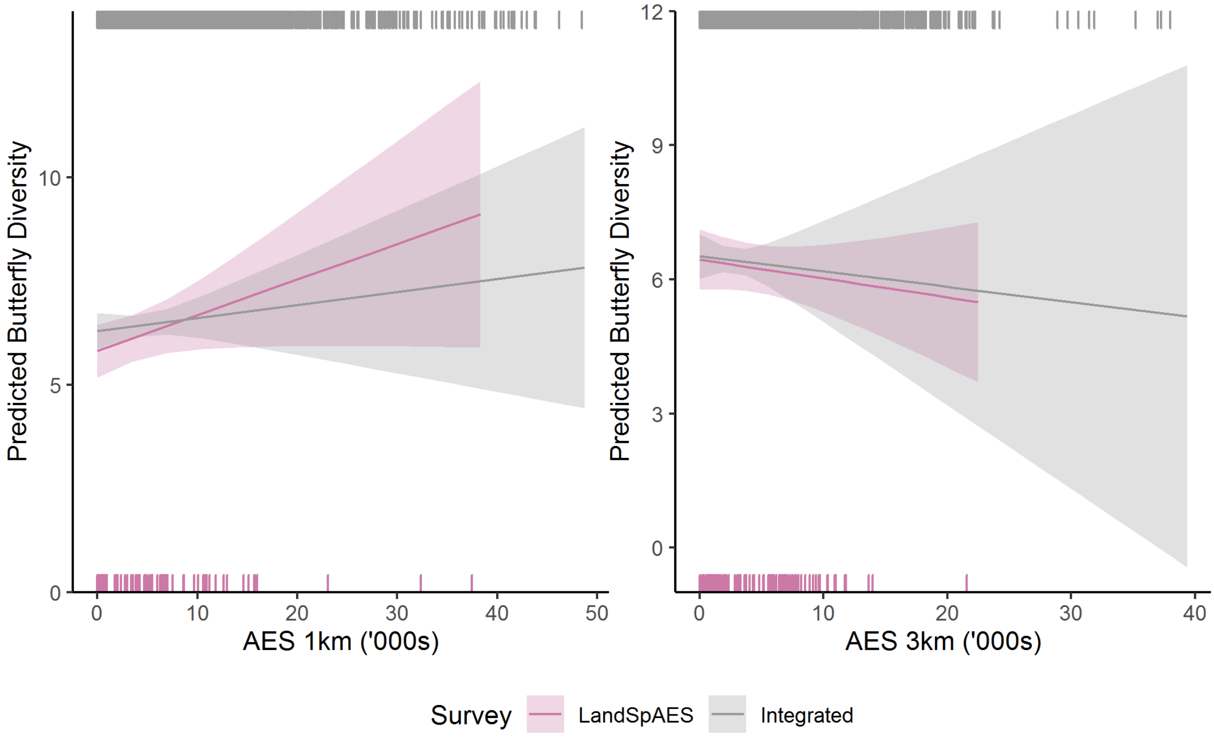

Figure 5.2.11. Comparison of predictions of butterfly diversity (exponential transformed Shannon index) in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES data and integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

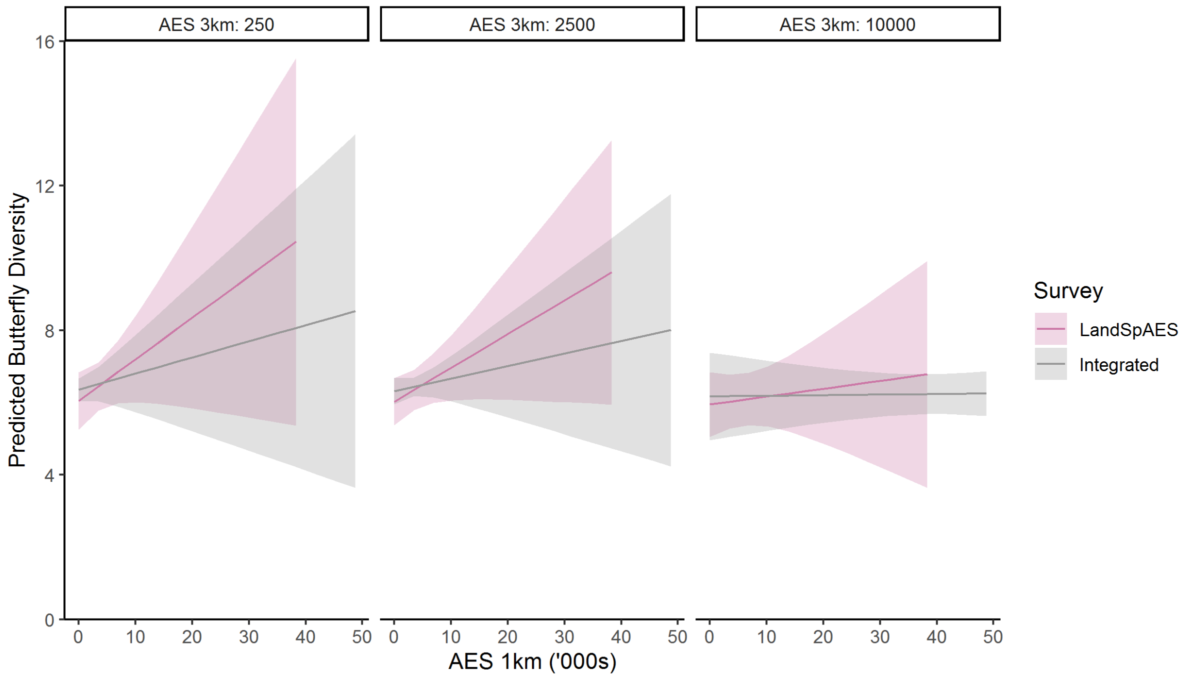

Figure 5.2.12. Predicted relationship between butterfly diversity (exponential transformed Shannon index) and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES model and integrated model. Shaded areas indicate confidence intervals around the prediction.

Evaluation of the integrated model suggested that integrated models had higher uncertainty than the LandSpAES model, shown by higher MAE, RMSE and coefficient of variation (Table 5.2.13). Integration decreased estimated standard errors on the local AES effect (Table 5.2.12) but increased error on the estimation of the landscape AES effect.

Table 5.2.13. Evaluation of integrated and LandSpAES models. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	MAE	RMSE	CV
LandSpAES	1.337	1.915	0.301
Integrated	5.601	5.755	3.001

5.2.4.3. Butterfly abundance

Evidence from individual scheme models showed good support for fitting an integrated model to butterfly abundance for LandSpAES and WCBS but not for LandSpAES and UKBMS. We therefore fit a model with scheme-specific intercept terms to only LandSpAES and WCBS datasets and did not use UKBMS for integrated modelling of butterfly abundance.

The integrated model showed a positive relationship with local and landscape AES gradients, a result also seen in the LandSpAES models (Table 5.2.14; Figures 5.2.13, 5.2.14). Uncertainty in predictions of AES effects was reduced at high levels of AES.

Table 5.2.14. Estimated relationships between butterfly abundance and AES gradients for LandSpAES and the integrated model. Estimated coefficients are shown ± standard error.

Model	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.164 ± 0.078	0.035	0.178 ± 0.044	<0.001	-0.157 ± 0.068	0.021
Integrated	0.152 ± 0.027	<0.001	0.117 ± 0.020	<0.001	-0.036 ± 0.011	0.002

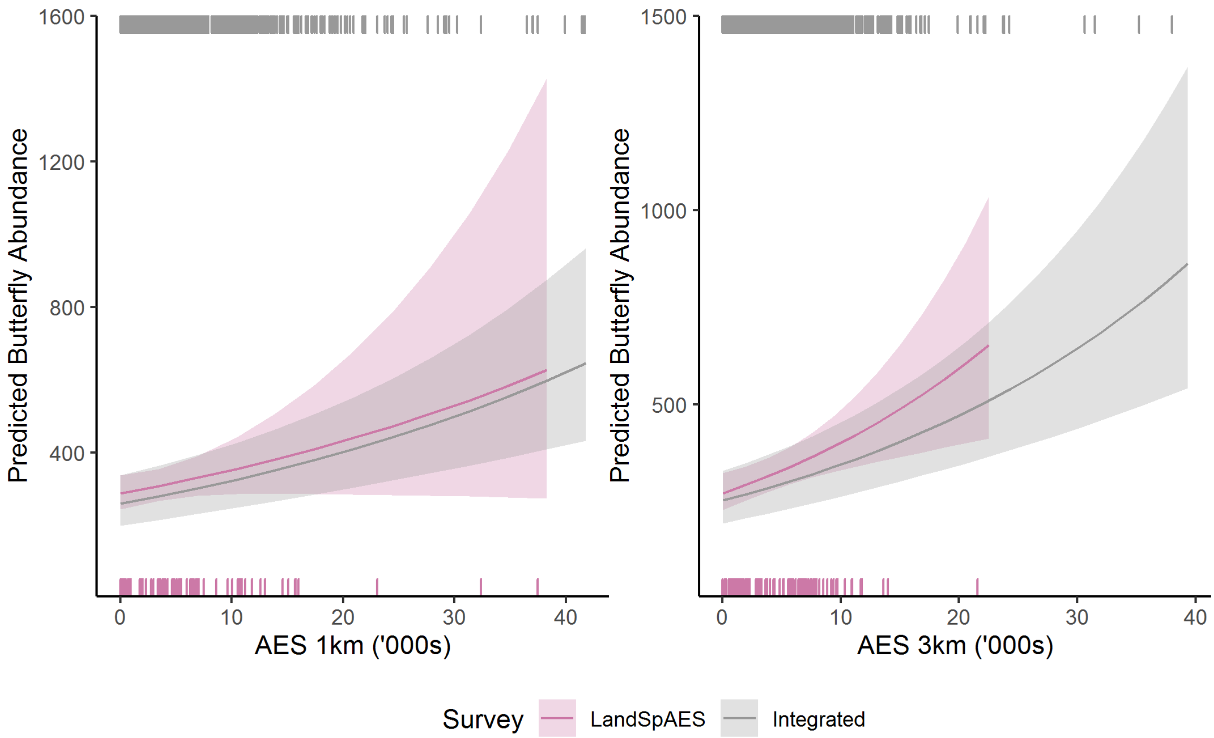

Figure 5.2.13. Comparison of predictions of butterfly abundance in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES data and integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

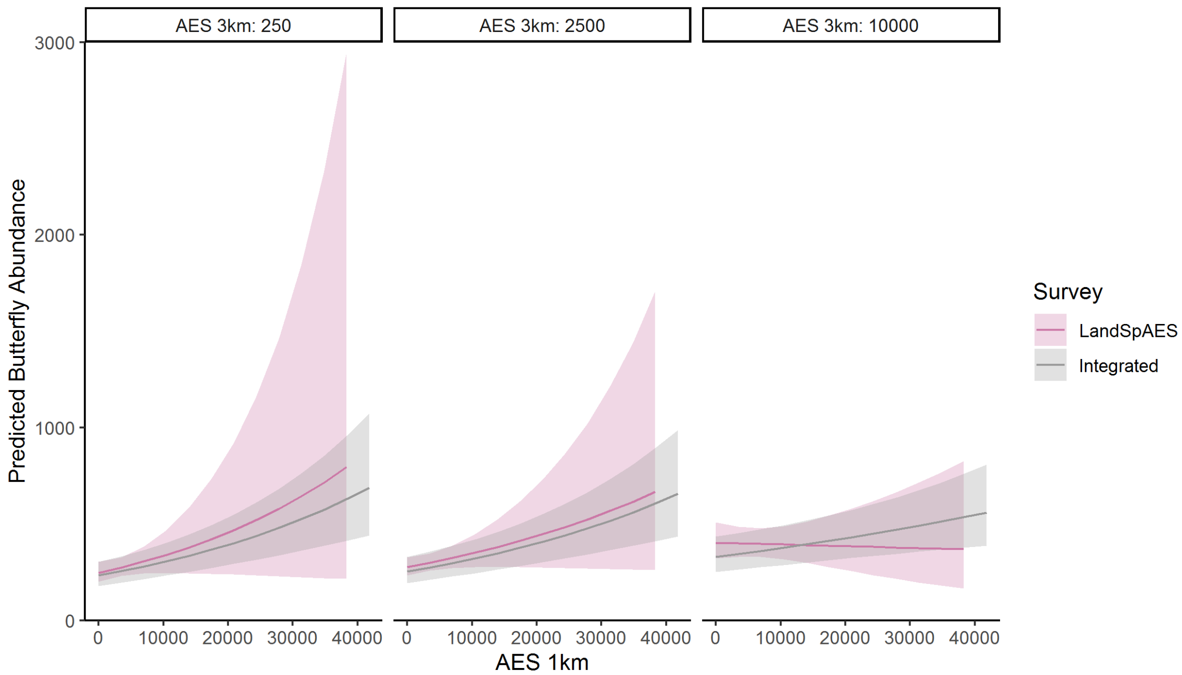

Figure 5.2.14. Predicted relationship between butterfly abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES model and integrated model. Shaded areas indicate confidence intervals around the prediction.

Evaluation of the integrated model showed lower MAE and RMSE, although slightly higher coefficient of variation (Table 5.2.15). The integrated model had increased precision in estimation of AES effects (smaller standard errors in Table 5.2.14).

Table 5.2.15. Evaluation of integrated and LandSpAES models. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	MAE	RMSE	CV
LandSpAES	310.796	387.974	1.125
Integrated	105.812	224.463	1.409

5.2.5. Discussion and summary of butterfly results

Overall, there was good evidence that the relationships observed between butterfly responses and AES gradients in the LandSpAES project can be found in the CitSci scheme datasets. Integrated models confirm that the relationships observed by integrating all three butterfly datasets, or the LandSpAES and WCBS data, give similar or better results than using LandSpAES data alone for richness and abundance responses. Benefits are particularly seen at high levels of AES, where the coverage of CitSci data is better than that of LandSpAES data.

For species richness, reduced uncertainty was only evident when the integrated analysis was restricted to combining LandSpAES and WCBS data, rather than using the data from all three buttefly surveys. There was evidence from the z-tests that the relationships between species richness and AES gradients were different between WCBS and UKBMS. Although the z-test results showed differences in coefficients between butterfly species richness and the landscape AES gradient across the three datasets, the direction of relationship with landscape AES gradient was positive for all datasets.

Integrated models for abundance were also restricted to WCBS and LandSpAES, as there was evidence of differences in responses between LandSpAES and UKBMS. It was not possible to fit integrated random slope models, which would have allowed the relationship with AES gradient to differ between datasets, for either butterfly species richness or abundance. This was due to issues with model convergence.

Uncertainty in estimation of AES effects was reduced for richness and abundance responses in the integrated models, indicating the models provided more confidence around estimating AES gradient effects, but not for diversity. Evidence from the individual scheme models suggested butterfly diversity responded differently between LandSpAES and the CitSci schemes.

In conclusion, butterflies are the taxa which have shown most similarity across datasets in the relationships between response variables and AES gradients. The benefits of integrated modelling are thus also shown most strongly for butterflies, as uncertainty was reduced through integrated modelling for two of the three response variables.

5.3 Bumblebees surveyed along transects

Bumblebees are recorded by LandSpAES and the BeeWalk bumblebee recording scheme along transects.

5.3.1. Accounting for differences between datasets

5.3.1.1. Survey unit and transect placement

BeeWalk transects are not restricted to a 1km square unit unlike LandSpAES transects (further details in scoping Section 3.2.4). For comparison with LandSpAES we assigned each BeeWalk transect to the 1km square in which the transect centroid occurred and attributed the AES scores and covariate data associated with that square. Multiple BeeWalk transects may originate from the same focal point. For analysis we combined multiple BeeWalk transects from the same focal 1km square.

BeeWalk transects also vary in terms of length, compared to LandSpAES transects which are all 2km long. BeeWalk transect length assigned to focal squares (may be aggregated across multiple transects) varied between 70 and 6,684 metres in the years of interest. Variation in transect length may be a key factor in explaining bumblebee abundance and therefore transect length was included in all models containing BeeWalk data.

5.3.1.2. Number of visits

The BeeWalk transects used in this work were visited between 1 and 18 times a year, compared to LandSpAES where transects are visited four times a year. To account for the potential for multiple visits we included a term for number of visits in all models including BeeWalk data.

5.3.1.3. Taxonomic identification differences

To enable comparisons of bumblebee responses from both schemes it was necessary to repeat the taxonomic aggregations in LandSpAES for BeeWalk data. It is challenging to separate *B. terrestris* workers from *B. lucorum* workers in the field and therefore these taxa are aggregated into a single aggregate taxon for calculation of species richness and diversity metrics. *Bombus magnus* and *cryptarum* were also included in this aggregate.

5.3.2. Explaining NCA variation

Using the PCA axes approach described in Section 4.3.2. we identified a number of axes which explained variation previously attributed to NCA for each response (Table 5.3.1). Replacing NCA random effect with PCA axes did not change interpretation of the LandSpAES models (Appendix 1 Table A3).

Table 5.3.1. Selected PCA axes for each response variable.

Response variable	PCA axes selected	
	LandSpAES	**BeeWalk**
Bumblebee richness	1, 2	1, 2, 6, 18
Bumblebee diversity	1, 2	1, 2, 11, 18
Bumblebee abundance	1, 2	1, 2, 26

5.3.3. Results of individual scheme models

5.3.3.1 Bumblebee species richness

Estimated relationships between bumblebee species richness and local (1km) and landscape (3km) AES gradients were similar between LandSpAES and BeeWalk, with both showing a small non-significant positive trend in relation to local and landscape AES gradients and a small non-significant negative interaction term. However, bumblebee species richness was not found to be significantly associated with either AES gradients in either analyses of LandSpAES or BeeWalk data.

Table 5.3.2. Estimated relationships between bumblebee richness and AES gradients for LandSpAES and BeeWalk. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.081 ± 0.064	0.208	0.006 ± 0.039	0.874	-0.074 ± 0.058	0.205
BeeWalk	0.025 ± 0.033	0.445	0.007 ± 0.023	0.744	-0.026 ± 0.02	0.185

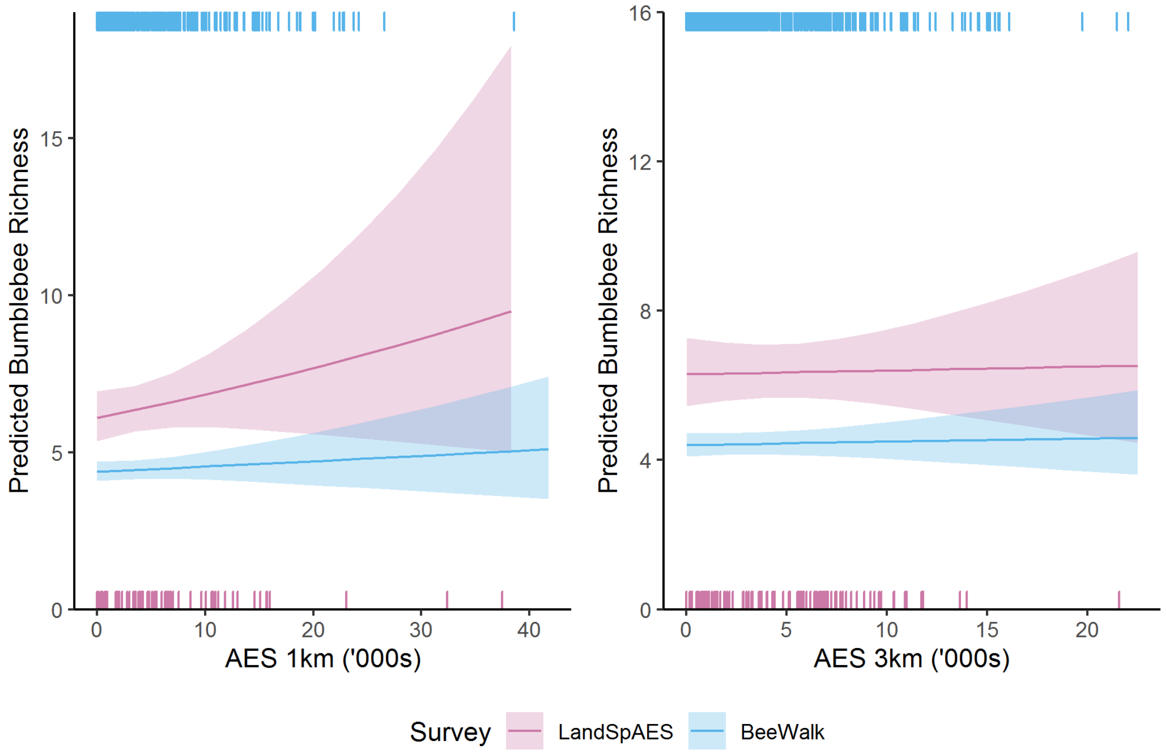

Figure 5.3.1. Predicted relationships between bumblebee species richness and local level (1km) and landscape level (3km) AES gradients for LandSpAES and BeeWalk. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

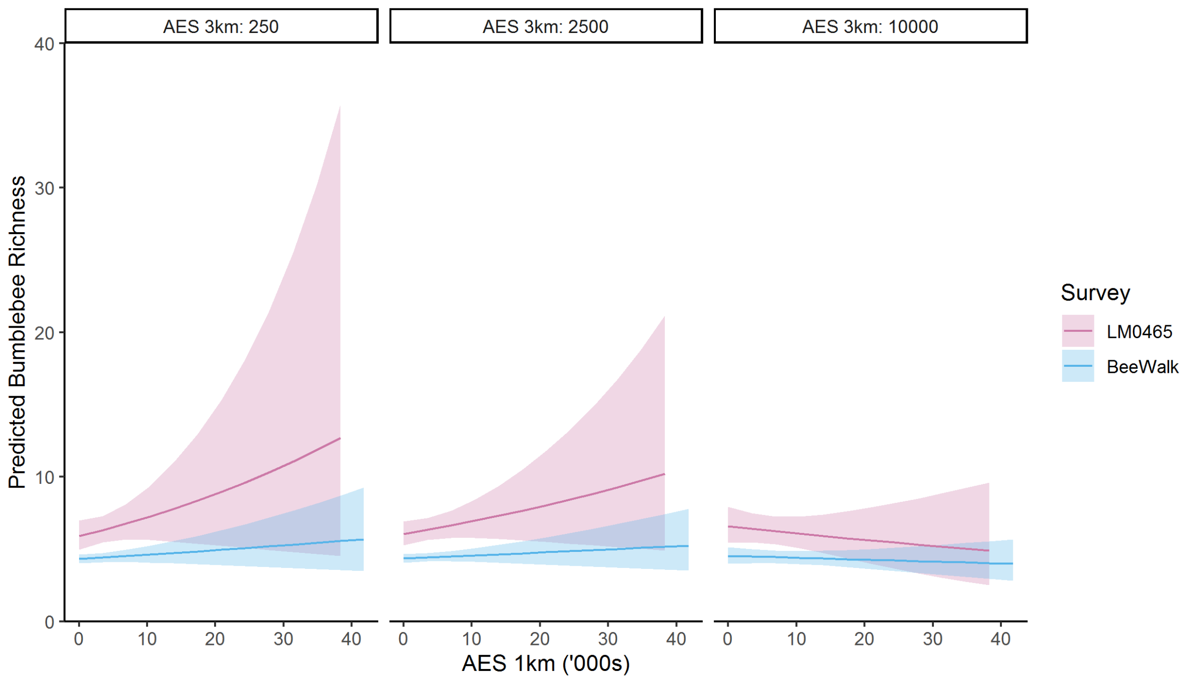

Figure 5.3.2. Predicted relationship between bumblebee species richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for LandSpAES and BeeWalk. Shaded areas indicate confidence intervals around the prediction.

The results of the z-tests confirmed that coefficient estimates were not significantly different between LandSpAES and BeeWalk (Table 5.3.3).

Table 5.3.3. Z-test results for comparisons of AES coefficients between LandSpAES and BeeWalk for bumblebee species richness.

Comparison	1km AES	3km AES	Interaction
LandSpAES - BeeWalk	z = 0.764, *P* = 0.445	z = -0.027, *P* = 0.978	z = -0.781, *P* = 0.435

5.3.3.2. Bumblebee diversity

Estimated relationships between bumblebee diversity and local (1km) and landscape (3km) AES gradients trended in different directions for LandSpAES and BeeWalk. However, neither LandSpAES nor BeeWalk demonstrated any significant relationships between bumblebee diversity (measured as exponential transformed Shannon index) and the local (1km) or landscape (3km) AES gradients (Table 5.3.4; Figures 5.3.3, 5.3.4). No significant interaction terms were found.

Table 5.3.4. Estimated relationships between bumblebee diversity (exponential transformed Shannon index) and AES gradients for LandSpAES and BeeWalk. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	-0.065 ± 0.16	0.683	0.034 ± 0.089	0.703	-0.038 ± 0.136	0.782
BeeWalk	0.072 ± 0.081	0.378	-0.03 ± 0.054	0.587	-0.082 ± 0.044	0.061

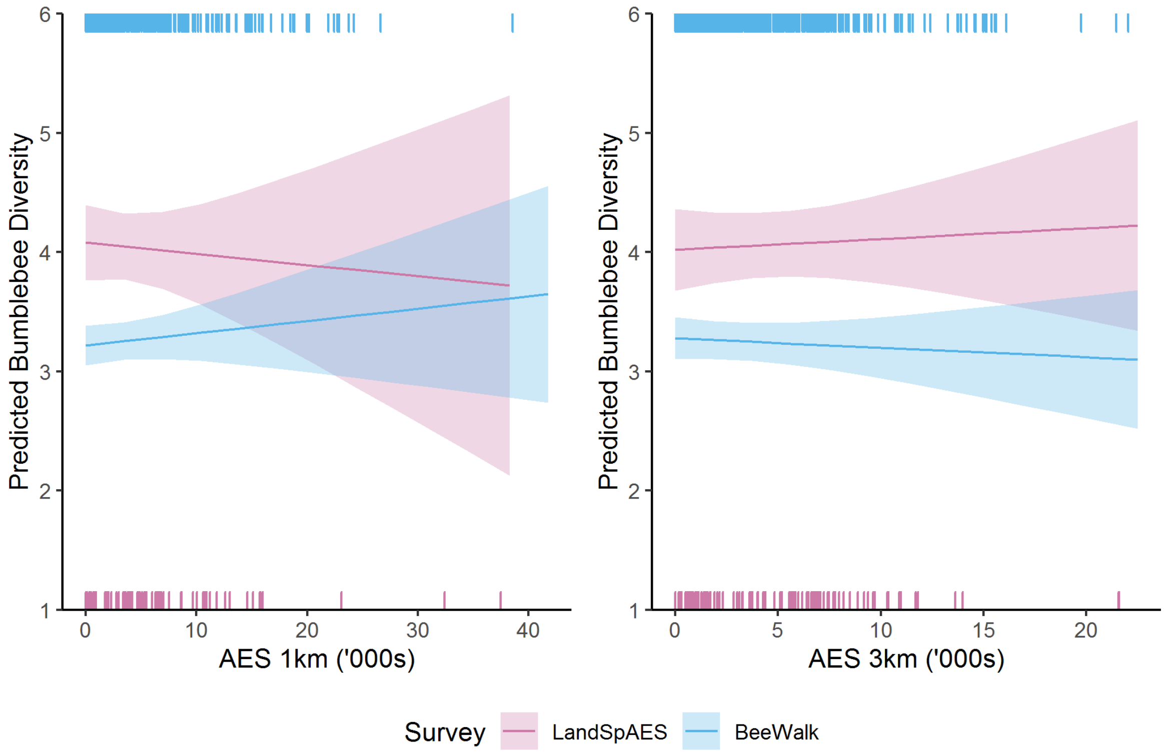

Figure 5.3.3. Predicted relationships between bumblebee diversity (exponential transformed Shannon index) and local level (1km) and landscape level (3km) AES gradient for LandSpAES and BeeWalk. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

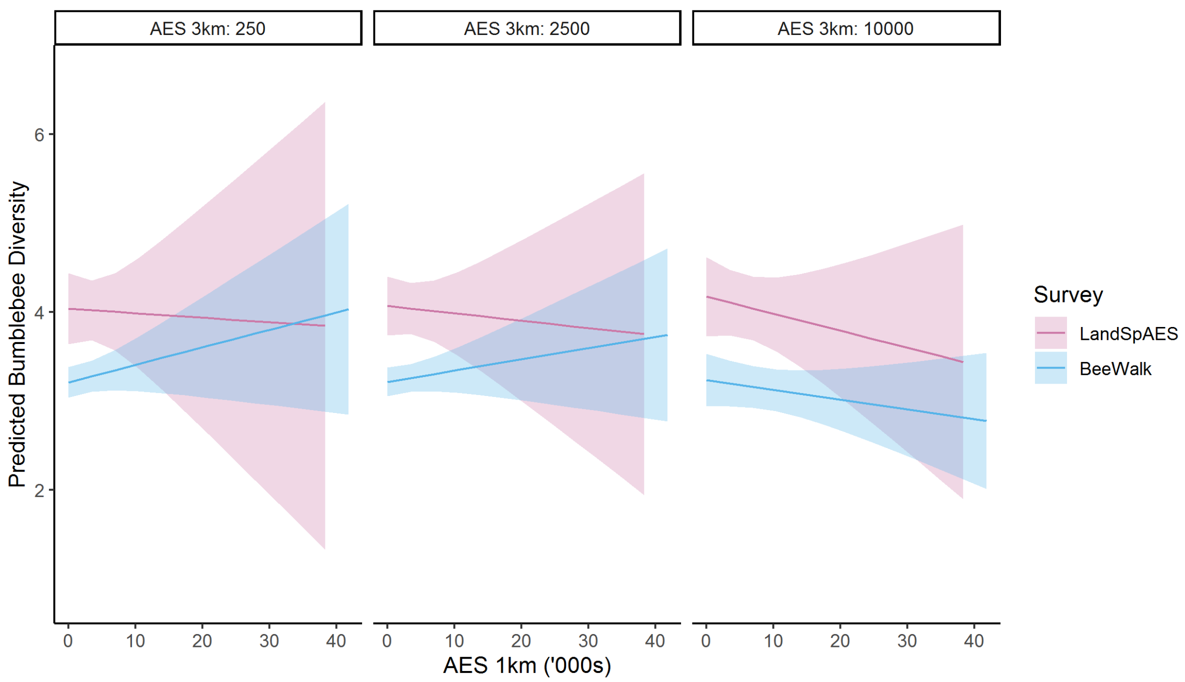

Figure 5.3.4. Predicted relationship between bumblebee diversity (exponential transformed Shannon index) and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BeeWalk. Shaded areas indicate confidence intervals around the prediction.

Results of the z-test confirmed similarity of AES coefficients between LandSpAES and BeeWalk bumblebee diversity models.

Table 5.3.5. Z-test results for comparisons of AES coefficients between LandSpAES and BeeWalk for bumblebee diversity (exponential transformed Shannon index).

Comparison	1km AES	3km AES	Interaction
LandSpAES - BeeWalk	z = -0.764, *P* = 0.445	z = 0.609, *P* = 0.543	z = 0.310, *P* = 0.757

5.3.3.3. Bumblebee abundance

Estimated relationships between bumblebee abundance and local (1km) and landscape (3km) trended in different directions in LandSpAES and BeeWalk (Table 5.3.6; Figures 5.3.5, 5.3.6). LandSpAES showed a borderline significant (*P* = 0.047) positive relationship between bumblebee abundance and local level AES. BeeWalk indicated a very slight negative trend in relation to local level AES, however this was estimated as close to zero. No AES relationships were significant in the BeeWalk data.

Table 5.3.6. Estimated relationships between bumblebee abundance and AES gradients for LandSpAES and BeeWalk. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.231 ± 0.116	0.047	-0.023 ± 0.065	0.723	-0.132 ± 0.099	0.183
BeeWalk	-0.015 ± 0.084	0.859	0.035 ± 0.056	0.532	-0.079 ± 0.045	0.082

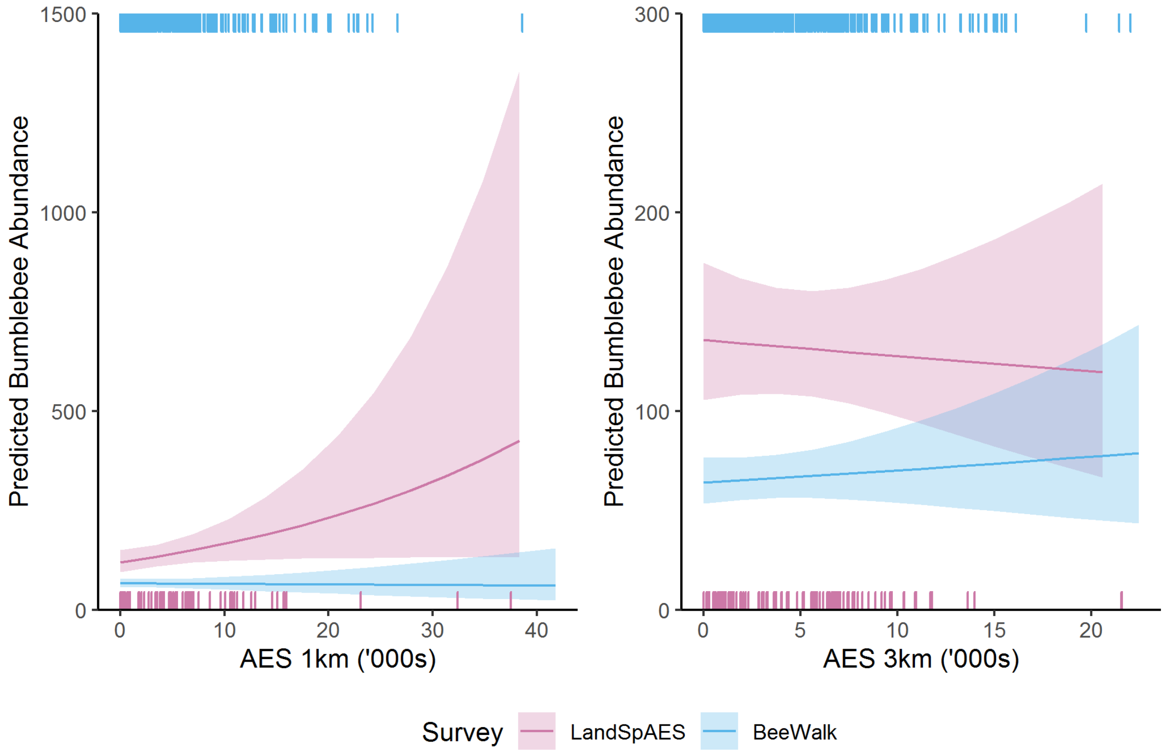

Figure 5.3.5. Predicted relationship between bumblebee abundance and local level (1km) AES gradient for LandSpAES and BeeWalk. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

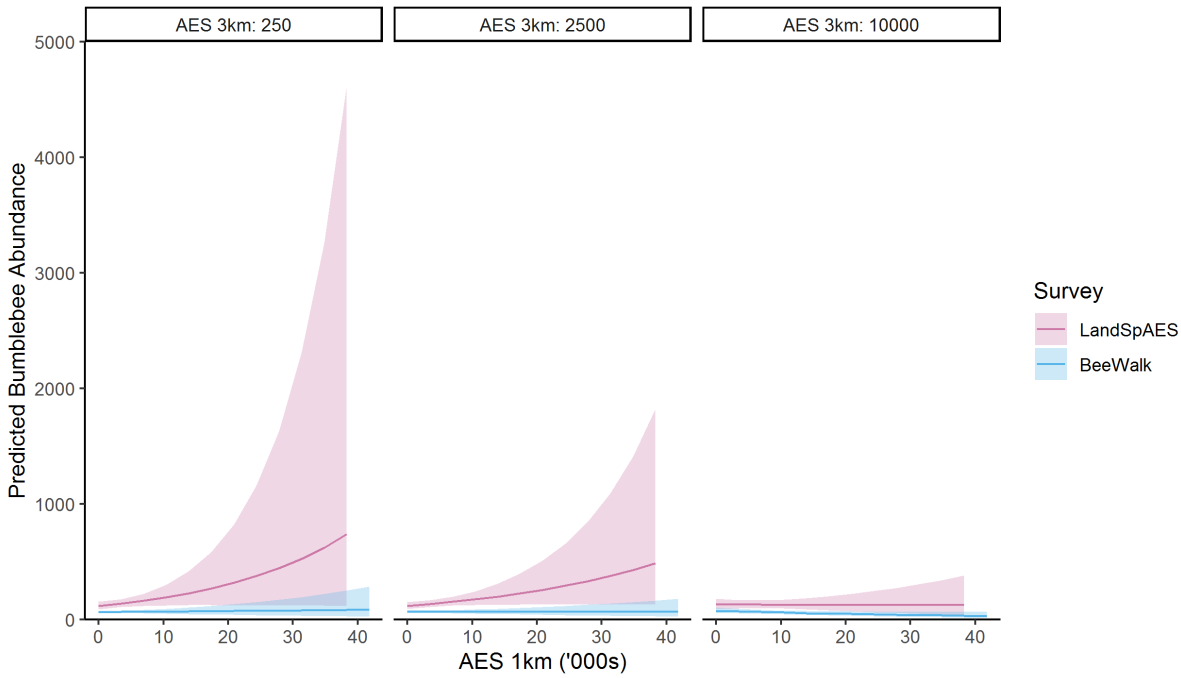

Figure 5.3.6. Predicted relationship between bumblebee abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for each of LandSpAES and BeeWalk. Shaded areas indicate confidence intervals around the prediction.

Despite some evidence of contrasting trends in bumblebee abundance between LandSpAES and BeeWalk, the z-test did not find any significant differences between coefficients in the two models. This is due to high uncertainty around coefficient estimates in both models.

Table 5.3.7. Z-test results for comparisons of AES coefficients between LandSpAES and BeeWalk for bumblebee abundance.

Comparison	1km AES	3km AES	Interaction
LandSpAES - BeeWalk	z = 1.719, *P* = 0.086	z = -0.676, *P* = 0.499	z = -0.491, *P* = 0.623

5.3.4. Integrated models

5.3.4.1. Bumblebee species richness

There was good evidence that relationships between AES gradients and bumblebee species richness were comparable between LandSpAES and BeeWalk. To include both datasets in a single model we fit an integrated model with random intercept to allow for variation in the mean number of bee species recorded in the two surveys.

The integrated model showed greater precision in estimation of AES effects (standard error terms in Table 5.3.8), however the integrated model did not predict any significant relationships between bumblebee species richness and AES gradients (Table 5.3.8; Figures 5.3.7, 5.3.8).

Table 5.3.8. Estimated relationships between bumblebee richness and AES gradients for LandSpAES and the integrated model. Estimated coefficients are shown ± standard error.

Model	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.081 ± 0.064	0.208	0.006 ± 0.039	0.874	-0.074 ± 0.058	0.205
Integrated	0.04 ± 0.028	0.150	0.004 ± 0.019	0.822	-0.033 ± 0.019	0.075

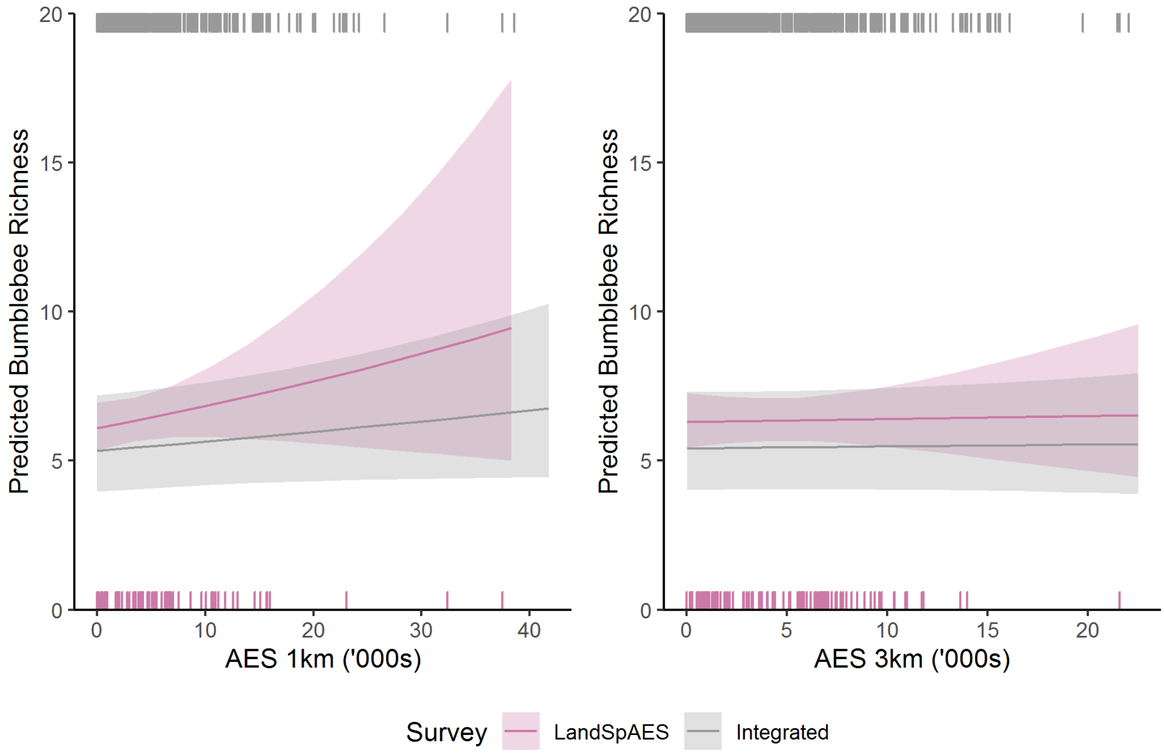

Figure 5.3.7. Comparison of predictions of bumblebee richness in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES data and integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of data along the AES gradients.

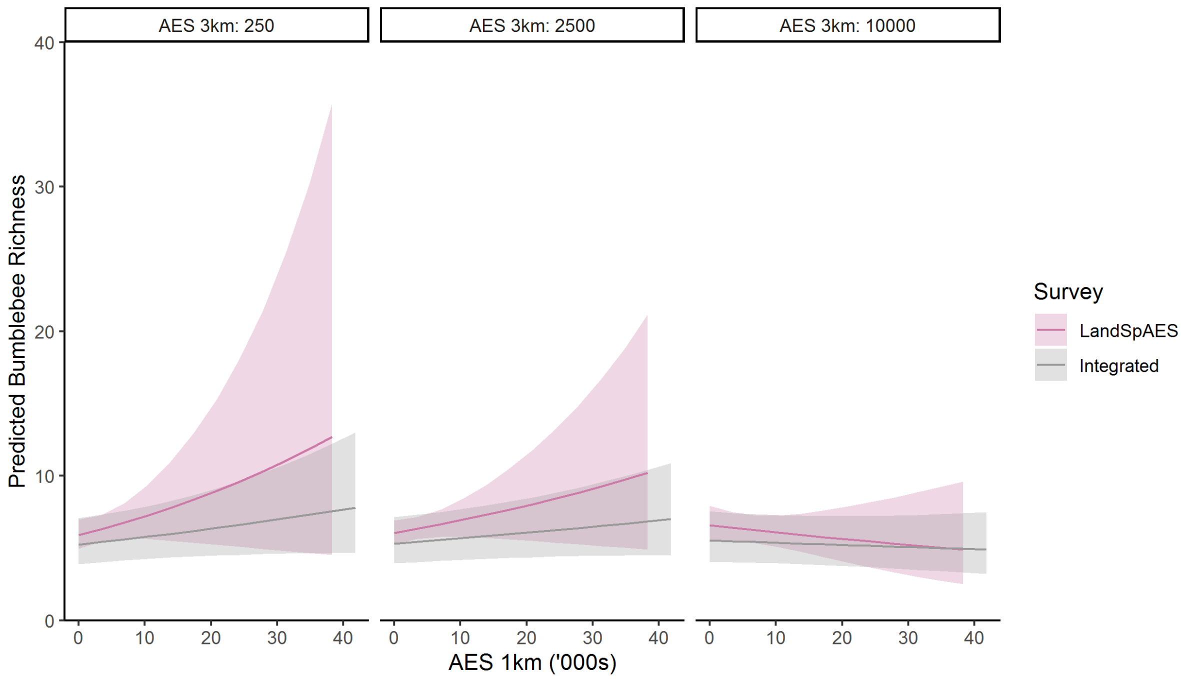

Figure 5.3.8. Predicted relationship between bumblebee richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES model and integrated model. Shaded areas indicate confidence intervals around the prediction.

Evaluation metrics for the integrated model showed lower median absolute error and root mean square error than the LandSpAES models, but a slightly higher coefficient of variation.

Table 5.2.9. Evaluation of integrated and LandSpAES models. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	MAE	RMSE	CV
LandSpAES	4.794	5.176	0.791
Integrated	3.434	3.807	0.834

5.3.4.2. Bumblebee diversity

Investigation of relationships between bumblebee diversity and AES gradients in the individual schemes showed small but non-significant differences in the direction of estimated relationships. We fit a random intercept model to integrate the two datasets. The integrated model found a significant interaction effect of 1km and 3km AES gradients on bumblebee diversity (Table 5.3.9; Figures 5.3.9, 5.3.10).

Table 5.3.9. Estimated relationships between bumblebee diversity (exponential transformed Shannon index) and AES gradients for LandSpAES and the integrated model. Estimated coefficients are shown ± standard error.

Model	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	-0.065 ± 0.160	0.683	0.034 ± 0.089	0.703	-0.038 ± 0.136	0.782
Integrated	0.066 ± 0.069	0.341	-0.02 ± 0.047	0.669	-0.086 ± 0.041	0.037

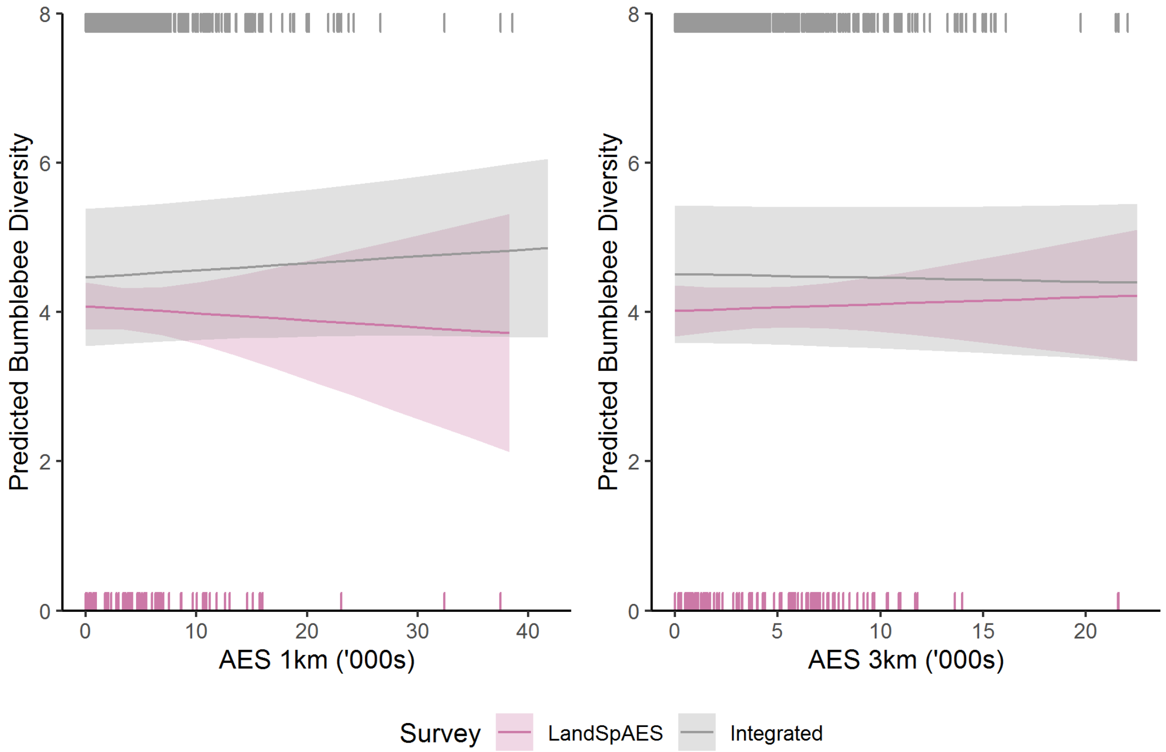

Figure 5.3.9. Comparison of predictions of bumblebee diversity (exponential transformed Shannon index) in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES data and integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

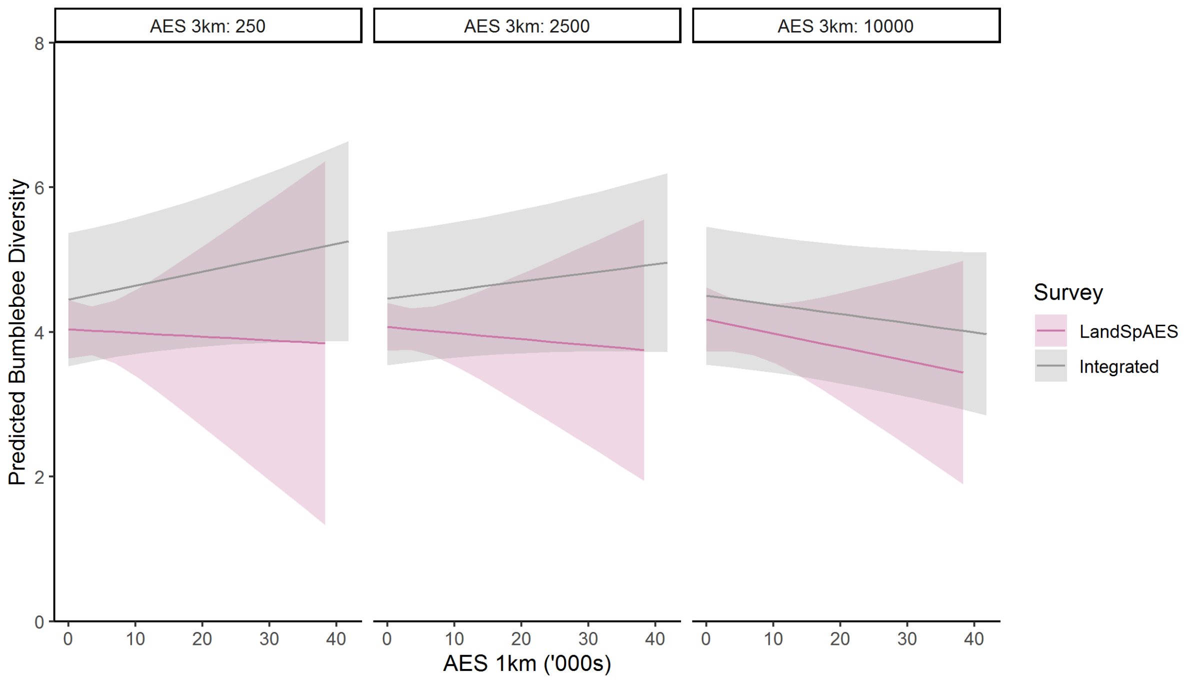

Figure 5.3.10. Predicted relationship between bumblebee diversity (exponential transformed Shannon index) and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES model and integrated model. Shaded areas indicate confidence intervals around the prediction.

Evaluation of the integrated model showed that all three metrics (MAE, RMSE and CV) were higher for the integrated model, suggesting this model had higher uncertainty than the model using only LandSpAES data.

Table 5.2.9. Evaluation of integrated and LandSpAES models. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	**MAE**	**RMSE**	**CV**
LandSpAES	2.606	2.534	1.999
Integrated	2.658	3.182	3.288

5.3.4.3. Bumblebee abundance

Evidence from individual models of LandSpAES and BeeWalk data suggested small but non-significant differences in the direction of estimates of AES gradient relationships with bumblebee abundance. We fit a random intercept model to the combined data. The integrated model showed a significant interaction effect of local and landscape AES gradients on bumblebee abundance, in contrast to the significant positive relationship with local level AES seen in the LandSpAES-only model (Table 5.3.10, Figures 5.3.11, 5.3.12).

Table 5.3.10. Estimated relationships between bumblebee abundance and AES gradients for LandSpAES and the integrated model. Estimated coefficients are shown ± standard error.

Model	**Local (1km)**	***P***	**Landscape (3km)**	***P***	**Interaction**	***P***
LandSpAES	0.231 ± 0.116	0.047	-0.023 ± 0.065	0.723	-0.132 ± 0.099	0.183
Integrated	0.113 ± 0.07	0.105	-0.009 ± 0.045	0.836	-0.096 ± 0.046	0.039

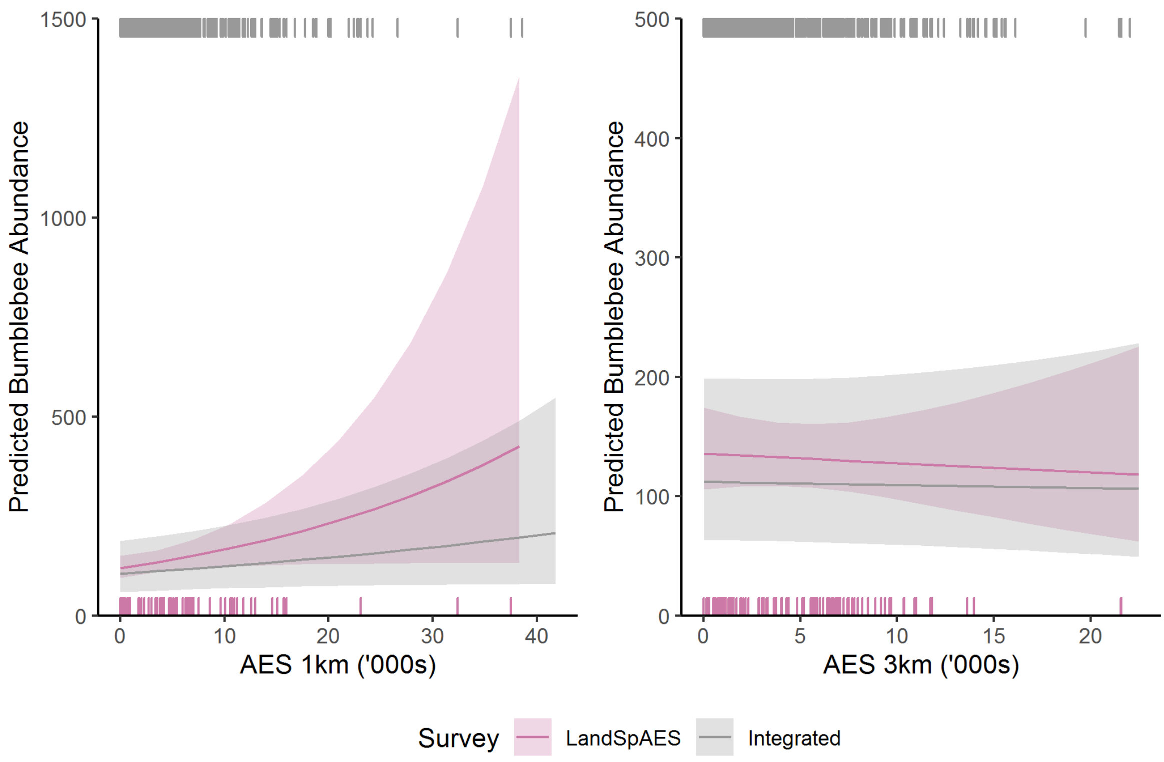

Figure 5.3.11. Comparison of predictions of bumblebee abundance in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES data and integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

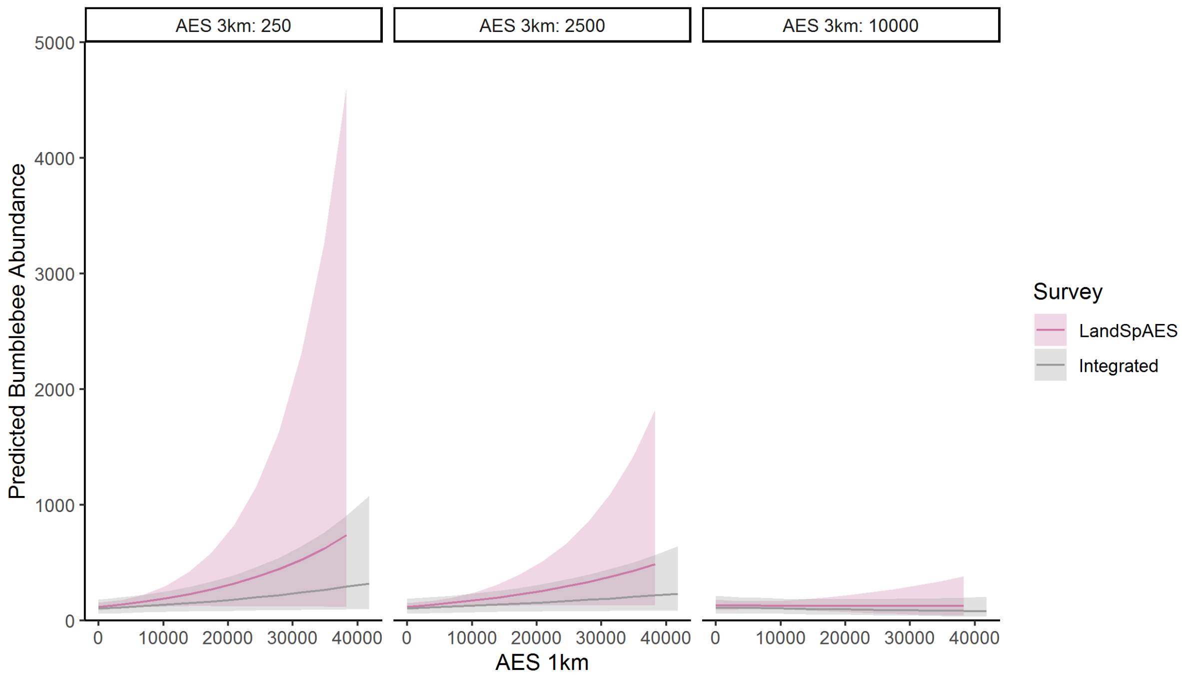

Figure 5.3.12. Predicted relationship between bumblebee abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES model and integrated model. Shaded areas indicate confidence intervals around the prediction.

Evaluation of the integrated model showed lower median absolute error and root mean square error but slightly higher coefficient of variation.

Table 5.2.9. Evaluation of integrated and LandSpAES models. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	MAE	RMSE	CV
LandSpAES	119.715	265.711	1.399
Integrated	51.056	176.786	1.649

5.3.5. Discussion and summary of bumblebee results

Relationships between bumblebee responses and AES gradients were similar between LandSpAES and BeeWalk for bumblebee richness, but some (non-significant) differences were seen in relationships with bumblebee diversity and abundance. BeeWalk models showed no significant relationships between any bumblebee response and AES gradients. LandSpAES models showed a just significant (P = 0.047) positive relationship between local level AES and bumblebee abundance. The z tests showed no significant differences in the AES gradient coefficients for any of the bumblebee responses, and so all three responses were used in integrated modelling.

The integrated models produced by combining LandSpAES and BeeWalk data showed a significant interaction effect of local and landscape AES gradients on both bumblebee diversity and abundance. No significant interaction effects of AES gradients were observed in the individual scheme models, though there was a trend towards interactions for the BeeWalks model for both diversity (P = 0.061) and abundance (P = 0.082).

Precision on the estimation of AES effects was increased for all responses by integrating LandSpAES and BeeWalk data, in terms of smaller standard errors. For bumblebee species richness and abundance, median absolute error and root mean square error were smaller in the integrated models, however the coefficient of variation increased slightly. The integrated models for these variables are therefore roughly equivalent to the LandSpAES models, in terms of uncertainty. For bumblebee diversity the integrated model led to an increase in uncertainty according to all three evaluation metrics, compared with the model using only LandSpAES data.

In addition to the conclusions from the modelling of AES gradient effects on BeeWalks and LandSpAES data, graphs in Section 5.3.3 show that species richness and abundance of bumblebees is consistently lower in the BeeWalks data than for the LandSpAES data, across the local and the landscape AES gradient. However, the confidence intervals for predictions of these response variables are large for the LandSpAES dataset, particularly at the high end of the local AES gradient. These differences might be due to the differences between the datasets in the survey unit and number of survey visits (see scoping Section 3.2.4 for details), and / or to differences between volunteer recorders and professional surveyors, though it is not possible to definitely attribute the differences to any one of these factors.

5.4 Bees and hoverflies surveyed using pan traps

Pan traps are used to collect pollinating insects in the PoMS CitSci scheme, which we can use to compare bumblebee, hoverfly and solitary bee diversity and abundance to LandSpAES results.

5.4.1. Accounting for protocol differences

There are several key differences in protocols between the two pan trap surveys, as well as some differences in how certain taxa are recorded.

5.4.1.1. Number of survey visits and pan traps

Both LandSpAES and PoMS have the same survey season and aim for the same frequency of four visits per year. However, the PoMS sites had fewer visits per year on average compared to the LandSpAES survey due to the volunteer-based nature of the PoMS survey, with around half of the year/site combinations having only one or two visits. This leads to there being fewer traps per year as well, as there is a strong correlation between number of visits and number of traps within PoMS (0.98). LandSpAES uses six pan traps per square while PoMS uses 5, however there is occasional disturbance of trap stations in both surveys. On average LandSpAES had 23 traps per site/year combination, while PoMS had only 12.

Each model had the number of pan traps included as a predictor to represent sampling effort, the number of visits was not also included to reduce collinearity within the model. Within LandSpAES the number of traps was an insignificant predictor of hoverfly richness, diversity or abundance but it was a significant (positive) predictor of all other variables in LandSpAES and all variables in PoMS.

5.4.1.2. Taxonomic identification differences

LandSpAES and PoMS had a few differences in the level of detail in the taxonomic identification of specimens, though in the majority of cases the same aggregations were used. The same aggregate taxonomic groupings were used for richness and diversity statistics to keep the differences in detail of taxonomy as minimal as possible, with the result that the only difference was *Bombus lucorum* and *Bombus terrestris* being recorded separately in LandSpAES and together in PoMS. Other taxonomic aggregations were consistent between surveys, and are detailed as follows:

- The *Sphaerophoria* females were only included in richness and diversity statistics in square/year combinations that had no other *Sphaerophoria* recorded.
- All *Cheilosia albitarsis* records were aggregated into *C. albitarsis sens.lat.*
- *Platycheirus peltatus*, *Platycheirus peltatus agg.* and *Platycheirus nielseni* were all combined into *P. peltatus agg.*
- *Platycheirus scutatus* and *Platycheirus scutatus sens. lat.* were all combined into *P. scutatus sens. lat.*

- Within PoMS there are records of *Nomada flava*, *Nomada penzeri sensu lato*, *Nomada panzeri sensu stricto* and *Nomada flava/panzer* which were all aggregated together for species richness and diversity. LandSpAES did not record these taxa.

5.4.2. Bumblebees surveyed using pan traps

5.4.2.1. Explaining NCA variation

Using the PCA axes approach described in Section 4.2, we identified a number of axes which explained variation previously attributed to NCA for each response. Replacing NCA random effect with PCA axes did not change interpretation of the LandSpAES models, all AES gradient effects were still non-significant, and the direction of the effect did not reverse.

Table 5.4.1. Selected PCA axes for each response variable.

Response variable	**PCA axes selected**	
	LandSpAES	**PoMS**
Bumblebee richness	1, 2	1, 2
Bumblebee diversity	1, 2	1, 2
Bumblebee abundance	1, 2, 11, 18	1, 2

5.4.2.2. Results of individual scheme models

5.4.2.2.1 Bumblebee species richness

For bumblebee species richness, we found differences in the relationships with local and landscape AES gradients between LandSpAES and PoMS data, particularly in the interaction effect between the two AES gradients. All schemes showed a non-significant relationship with local AES, and a non-significant relationship with landscape AES (Figure 5.4.1). However, LandSpAES showed a non-significant positive trend towards an interaction term while PoMS showed a significant negative interaction term (Table 5.4.2, Figure 5.4.3). In PoMS, the interaction term indicated that the relationship between species richness and local (1km) AES was more strongly positive at lower levels of landscape (3km) AES, while the opposite was true for LandSpAES.

All following prediction plots are standardized to be the prediction when 15 pan traps per year were used, as this was the average number of pan traps across the two surveys.

Table 5.4.2. Estimated relationships between bumblebee richness and AES gradients for LandSpAES and PoMS. Estimated coefficients are shown ± standard error.

Survey	**Local (1km)**	***P***	**Landscape (3km)**	***P***	**Interaction**	***P***
LandSpAES	-0.083 ± 0.076	0.280	-0.001 ± 0.044	0.989	0.106 ± 0.065	0.101
PoMS	-0.039 ± 0.076	0.608	0.019 ± 0.083	0.818	-0.172 ± 0.072	0.017

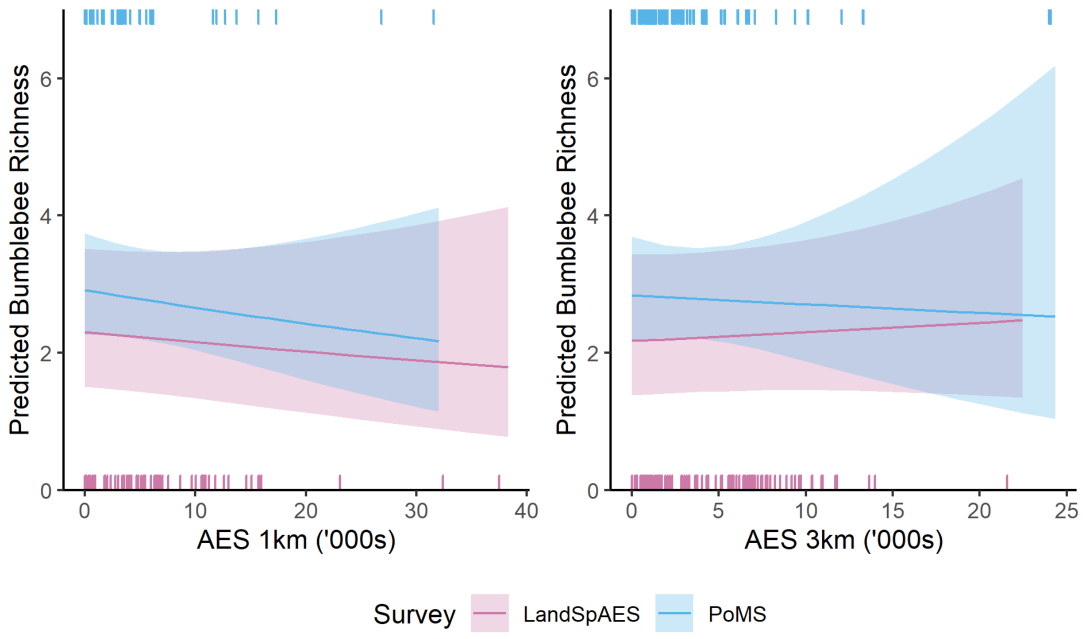

Figure 5.4.1. Predicted relationship between bumblebee species richness and local level (1km, left) and landscape level (3km, right) AES gradients for LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

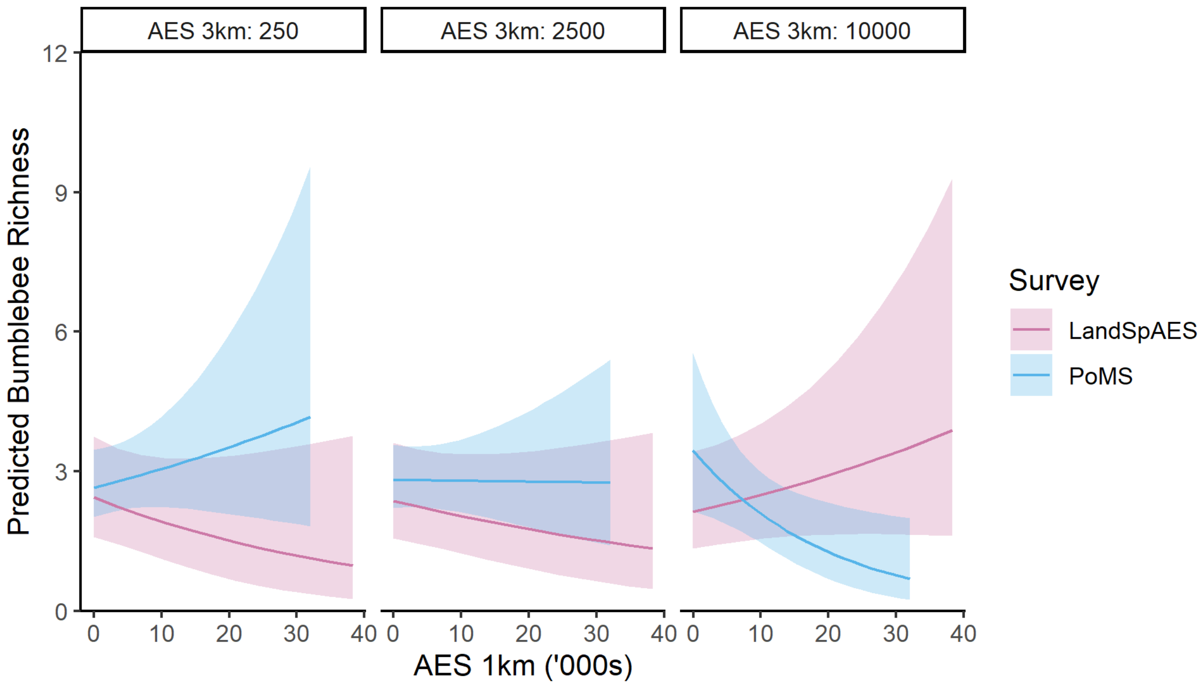

Figure 5.4.2. Predicted relationship between bumblebee species richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for both LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction.

The difference between the AES gradient interaction effect was confirmed to be significant by the z test (Table 5.4.3). Due to these differences in the relationship between bumblebee species richness and AES gradient effects across the two datasets, shown in the Figures 5.4.1 and 5.4.2 and confirmed by the z-test results, integrated modelling was not attempted for this response variable.

Table 5.4.3. Z-test results for comparisons of AES coefficients between LandSpAES and PoMS for bumblebee species richness.

Comparison	1km AES	3km AES	Interaction
LandSpAES - PoMS	z = -0.406, *P* = 0.685	z = -0.210, *P* = 0.834	z = -2.875, *P* = 0.004

5.4.2.2.2. Bumblebee diversity

For bumblebee Shannon diversity we also found no significant relationships with the AES gradients between LandSpAES and PoMS. All schemes showed non-significant relationships with local AES and landscape AES (Figure 5.4.3). However, LandSpAES showed a positive interaction term while PoMS showed a negative interaction term (Figure 5.4.6). Unlike in the species richness model described above, both of these interaction terms were non-significant at *P* = 0.12 and *P* = 0.13 for LandSpAES and PoMS respectively (Table 5.4.4). For PoMS data, the interaction term indicated that the relationship between richness and local (1km) AES was more strongly positive at lower levels of landscape (3km) AES, while the opposite was true for LandSpAES. However, the large confidence intervals and lack of significant AES gradient effects make the directions of these relationships relatively uncertain for both datasets.

Table 5.4.4. Estimated relationships between bumblebee Shannon diversity and AES gradients for LandSpAES and PoMS. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	-0.052 ± 0.069	0.455	0.038 ± 0.039	0.329	0.092 ± 0.059	0.123
PoMS	-0.03 ± 0.054	0.586	0.002 ± 0.057	0.969	-0.063 ± 0.041	0.126

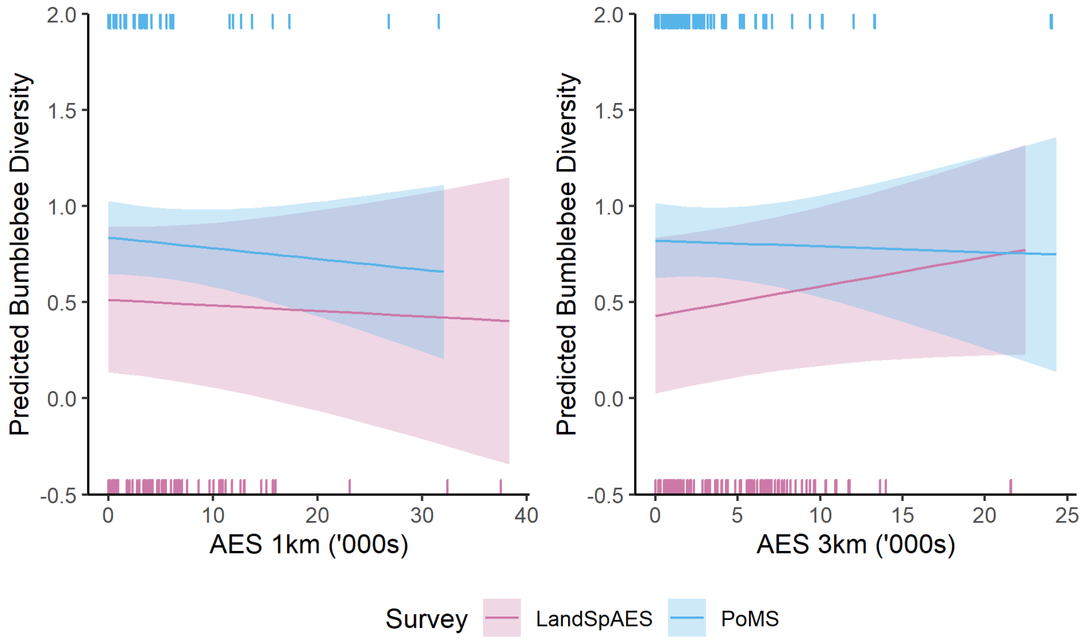

Figure 5.4.3. Predicted relationship between bumblebee Shannon diversity and local level (1km, left) and landscape level (3km, right) AES gradients for LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

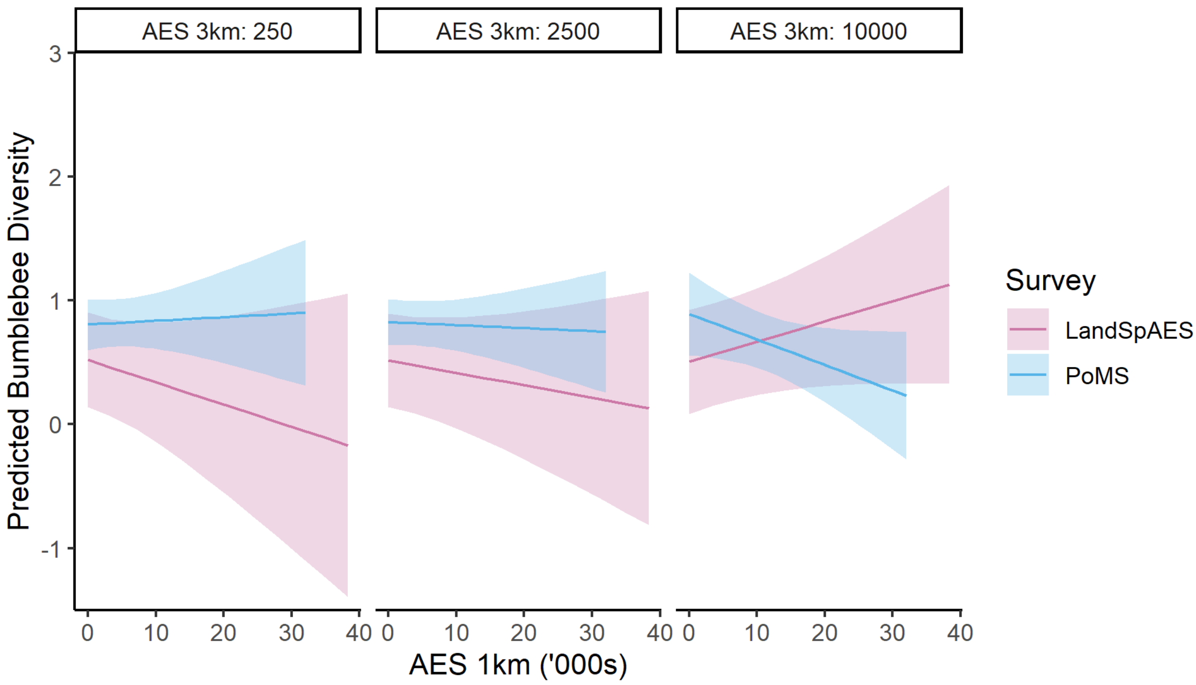

Figure 5.4.4. Predicted relationship between bumblebee Shannon diversity and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for both LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction.

The difference in responses to the AES gradient interaction was confirmed to be significant by the z test (Table 5.4.5). As for bumblebee species richness, it was decided not to attempt integrated modelling for bumblebee diversity, due to these differences in the datasets.

Table 5.4.5. Z-test results for comparisons of AES coefficients between LandSpAES and PoMS for bumblebee diversity.

Comparison	1km AES	3km AES	Interaction
LandSpAES - PoMS	z = -0.252, *P* = 0.801	z =0.519, *P* = 0.604	z = 2.153, *P* = 0.031

5.4.2.2.3. Bumblebee abundance

For bumblebee abundance we also found differences in the relationships with local and landscape AES gradients between LandSpAES and PoMS, again particularly in the interaction effect between the two AES gradients. All schemes showed non-significant relationships with local AES and landscape AES (Figure 5.4.5), and the confidence intervals are very large. LandSpAES data showed a non-significant positive interaction term while PoMS showed a significant negative interaction term (Table 5.4.6, Figure 5.4.6). In PoMS, the interaction term indicated that the relationship between abundance and local (1km) AES was more strongly positive at lower levels of landscape (3km) AES, while the opposite was true for LandSpAES.

Both surveys recorded similar abundances of bumblebees, once survey effort was fixed at 15 pan traps per year.

Table 5.4.6. Estimated relationships between bumblebee abundance and AES gradients for LandSpAES and PoMS. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	-0.157 ± 0.103	0.128	-0.04 ± 0.058	0.495	0.119 ± 0.088	0.174
PoMS	-0.026 ± 0.107	0.807	0.059 ± 0.121	0.626	-0.269 ± 0.094	0.004

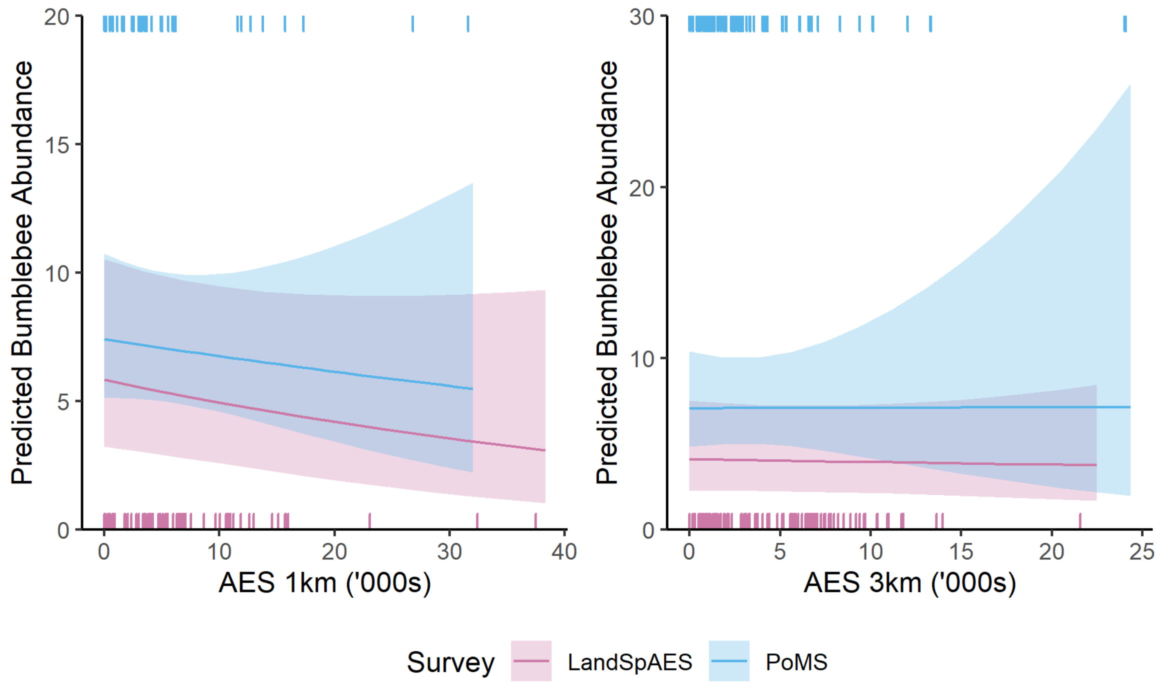

Figure 5.4.5. Predicted relationship between bumblebee abundance and local level (1km, left) and landscape level (3km, right) AES gradients for LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

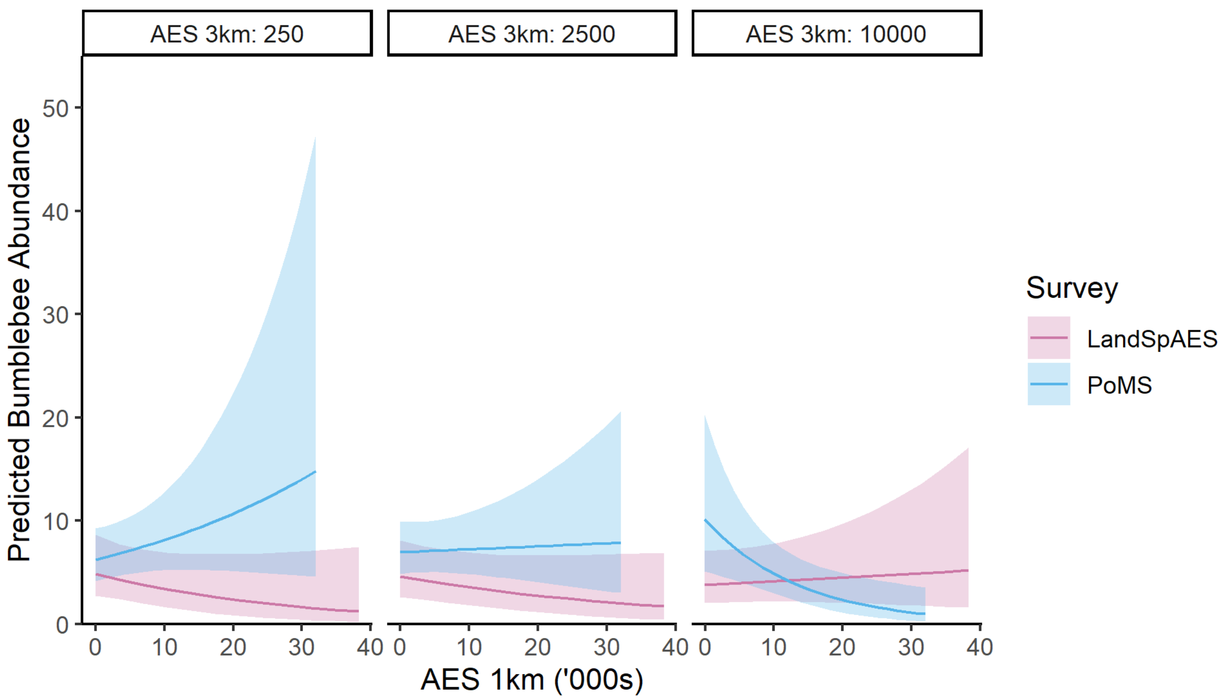

Figure 5.4.6. Predicted relationship between bumblebee abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for both LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction.

The difference in the responses of the two datasets to the AES gradient interaction was confirmed to be significant by the z test (Table 5.4.7).

Table 5.4.7. Z-test results for comparisons of AES coefficients between LandSpAES and PoMS for bumblebee abundance.

Comparison	**1km AES**	**3km AES**	**Interaction**
LandSpAES - PoMS	z = -0.877, *P* = 0.381	z = -0.734, *P* = 0.463	z = 3.022, *P* = 0.003

5.4.2.3 Discussion of bumblebee results

The bumblebee response variables, from data collected using pan trap surveys, showed strong differences between PoMS and LandSpAES datasets in their relationships with the AES gradients. This made it unfeasible to use any of the bumblebee pan trap responses in integrated models. In addition, the confidence intervals were large for all bumblebee pan trap responses, and no significant effects were found of AES gradients on bumblebee responses from the LandSpAES dataset.

For bumblebees surveyed with pan traps, the main differences between the two datasets were in the AES interaction effects. The PoMS data showed a negative interaction effect, such that the local AES score had a negative impact on bumblebee richness, diversity and abundance at high landscape AES scores while LandSpAES showed no such effect. The scoping showed that there were very few sites in PoMS with low local AES and high landscape AES so this interaction may be driven by a small number of sites.

5.4.3. Hoverflies

5.4.3.1. Explaining NCA variation

Using the PCA axes approach described in Section 4.2, we identified a number of axes which explained variation previously attributed to NCA for each response. Replacing NCA random effect with PCA axes did not change interpretation of the LandSpAES models, all AES gradient parameters were still non-significant. In some cases the direction of the effect reversed, but only in those models where parameter estimates were very near 0 and the total magnitude of the change was always less than 0.05.

Table 5.4.8. Selected PCA axes for each response variable.

Response variable	**PCA axes selected**	
	LandSpAES	**PoMS**
Hoverfly richness	1, 2	1, 2
Hoverfly diversity	1, 2	1, 2
Hoverfly abundance	1, 2, 26	1, 2

5.4.3.2. Results of individual scheme models

5.4.3.2.1 Hoverfly species richness

For hoverfly species richness, there were differences in the relationships with local and landscape AES gradients between LandSpAES and PoMS. LandSpAES showed a non-significant relationship with local AES, while PoMS showed a significant negative relationship with local AES (Table 5.4.9, Figures 5.4.7). Both schemes showed a non-significant relationship with landscape AES (Figure 5.4.7), and a non-significant interaction between local and landscape AES (Table 5.4.9, Figure 5.4.8).

On average, LandSpAES records slightly more species of hoverfly per year when standardized by number of pan traps. All following prediction plots are standardized to be the prediction when 15 pan traps per year were used.

Table 5.4.9. Estimated relationships between hoverfly richness and AES gradients for LandSpAES and PoMS. Estimated coefficients are shown ± standard error.

Survey	**Local (1km)**	***P***	**Landscape (3km)**	***P***	**Interaction**	***P***
LandSpAES	0.019 ± 0.063	0.760	-0.04 ± 0.036	0.270	-0.032 ± 0.055	0.554
PoMS	-0.221 ± 0.072	0.002	-0.01 ± 0.066	0.882	0.039 ± 0.05	0.436

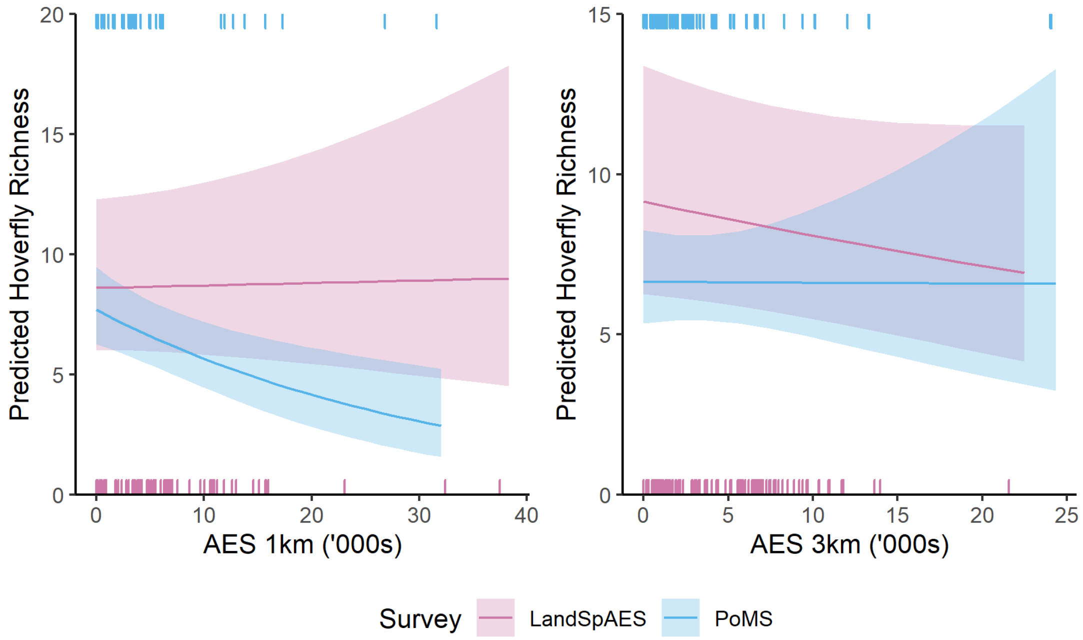

Figure 5.4.7. Predicted relationship between hoverfly species richness and local level (1km, left) and landscape level (3km, right) AES gradients for LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

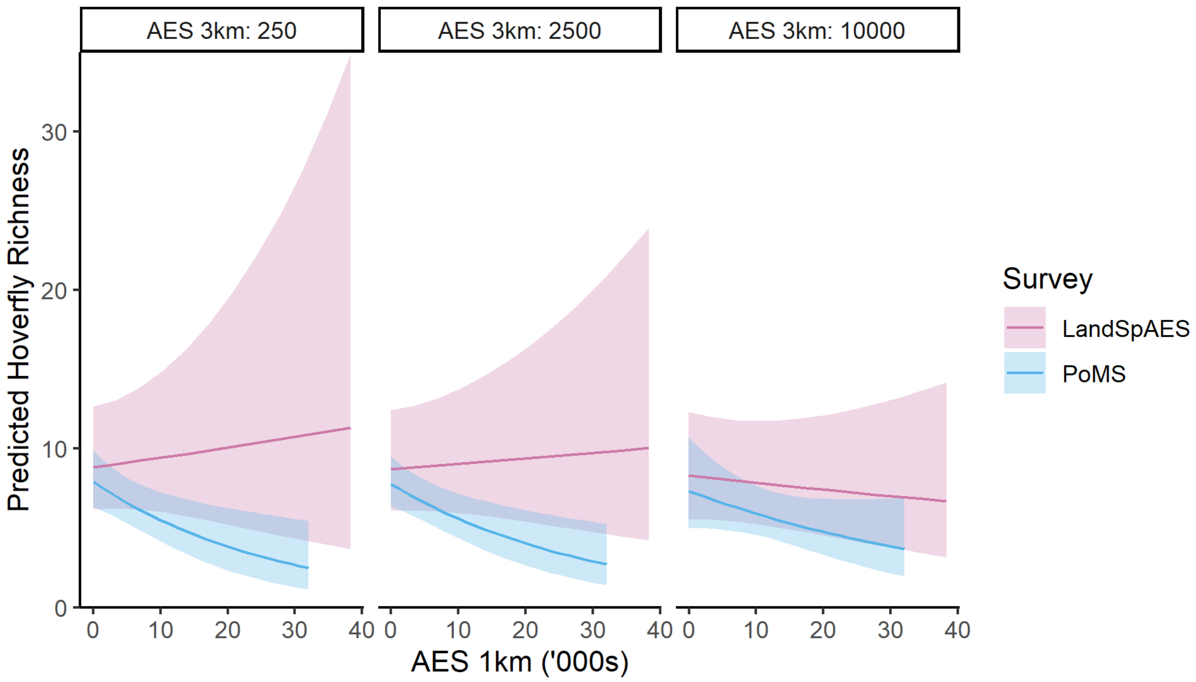

Figure 5.4.8. Predicted relationship between hoverfly species richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for both LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction.

The difference between the AES local gradient effects was confirmed to be significant by the z test (Table 5.4.10). Due to these differences between LandSpAES and PoMS, integrated modelling was not attempted for hoverfly species richness.

Table 5.4.10. Z-test results for comparisons of AES coefficients between LandSpAES and PoMS for hoverfly richness.

Comparison	**1km AES**	**3km AES**	**Interaction**
LandSpAES - PoMS	z = 2.501, *P* = 0.012	z = -0.396, *P* = 0.692	z = -0.962, *P* = 0.336

5.4.3.2.2. Hoverfly diversity

For hoverfly Shannon diversity we also found differences in the relationships with local and landscape AES gradients between LandSpAES and PoMS. PoMS again showed a significant negative relationship of local AES with hoverfly diversity, while LandSpAES showed no significant relationship with local AES (Table 5.4.11, Figure 5.4.9). Both schemes showed a non-significant relationship with landscape AES (Figure 5.4.9), and no significant interaction effect (Figure 5.4.10).

Table 5.4.11. Estimated relationships between hoverfly Shannon diversity and AES gradients for LandSpAES and PoMS. Estimated coefficients are shown ± standard error.

Survey	**Local (1km)**	***P***	**Landscape (3km)**	***P***	**Interaction**	***P***
LandSpAES	0.02 ± 0.07	0.775	-0.007 ± 0.04	0.863	-0.011 ± 0.06	0.859
PoMS	-0.185 ± 0.059	0.002	-0.035 ± 0.062	0.580	0.052 ± 0.044	0.246

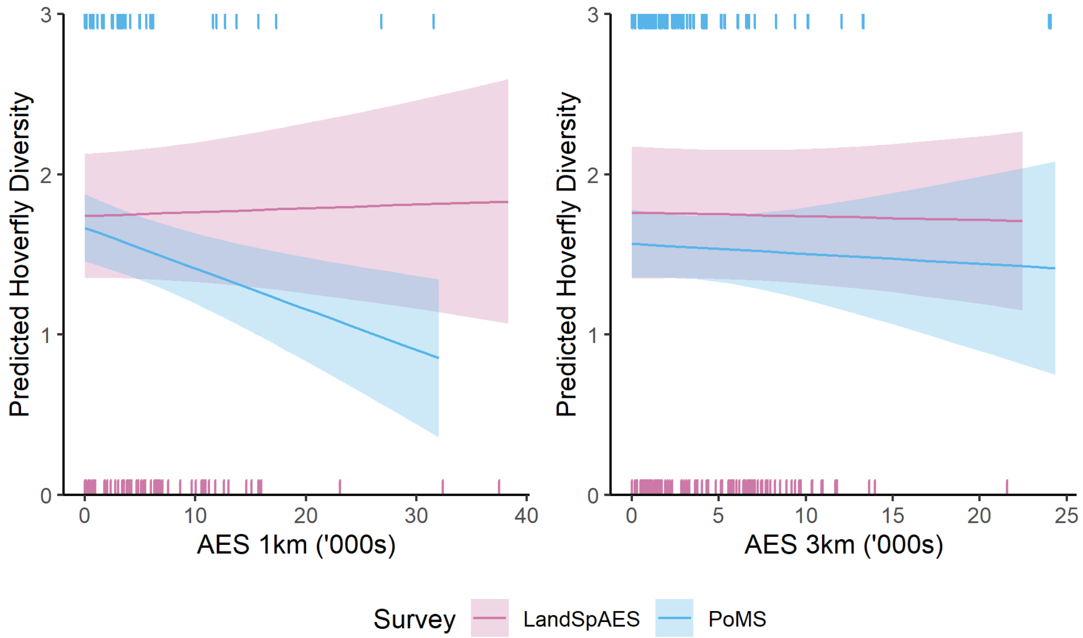

Figure 5.4.9. Predicted relationship between hoverfly Shannon diversity and local level (1km, left) and landscape level (3km, right) AES gradients for LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

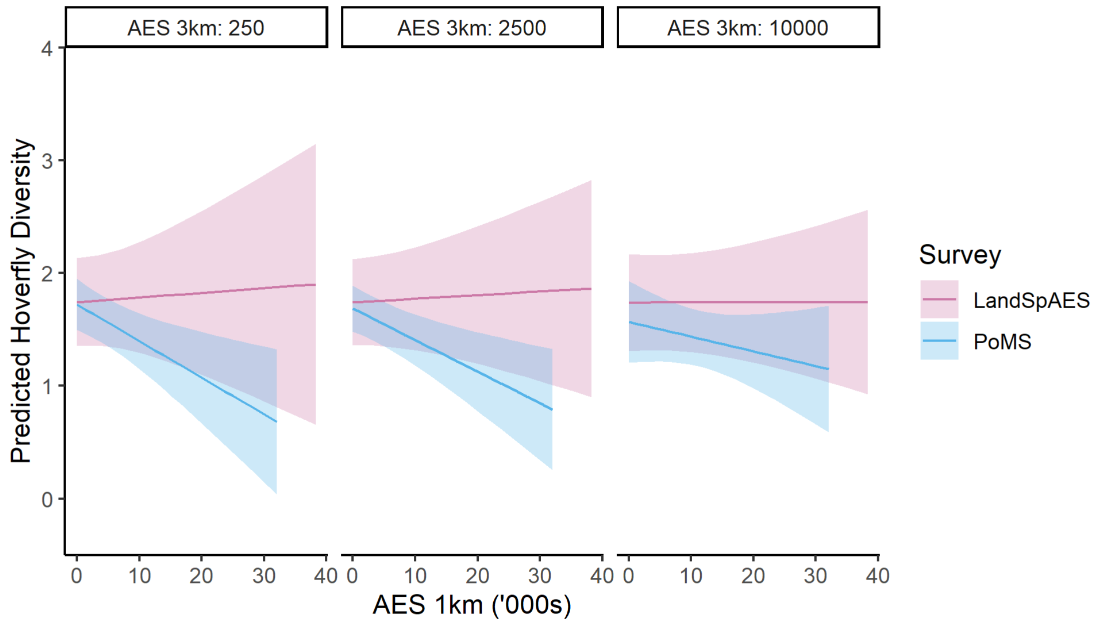

Figure 5.4.10. Predicted relationship between hoverfly Shannon diversity and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for both LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction.

The difference between the local AES gradient effects was confirmed to be significant by the z test (Table 5.4.12). As for hoverfly species richness, integrated modelling was not attempted for hoverfly diversity, due to the differences in AES gradient effects between the two datasets.

Table 5.4.12. Z-test results for comparisons of AES coefficients between LandSpAES and PoMS for hoverfly diversity.

Comparison	1km AES	3km AES	Interaction
LandSpAES - PoMS	z = 2.227, P = 0.026	z = 0.376, P = 0.707	z = -0.837, P = 0.403

5.4.3.2.3. Hoverfly abundance

For hoverfly abundance we also found differences in the relationships with local and landscape AES gradients between LandSpAES and PoMS. LandSpAES hoverfly abundance showed no relationship with local AES gradient, while PoMS data showed a significant negative relationship with local AES (Table 5.4.13, Figure 5.4.11). Neither survey showed a significant relationship with landscape AES gradient, however LandSpAES showed a negative trend with increasing landscape AES (Table 5.4.13, Figure 5.4.11). LandSpAES and PoMS also showed opposing non-significant trends with the interaction term, resulting in the impact of the local AES gradient being weakly negative at high levels of landscape AES in both surveys despite the difference in local AES effect at low landscape AES (Figure 5.4.12).

Table 5.4.13. Estimated relationships between hoverfly abundance and AES gradients for LandSpAES and PoMS. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.005 ± 0.122	0.968	-0.108 ± 0.071	0.126	-0.145 ± 0.105	0.167
PoMS	-0.368 ± 0.104	<0.001	-0.012 ± 0.101	0.902	0.083 ± 0.074	0.262

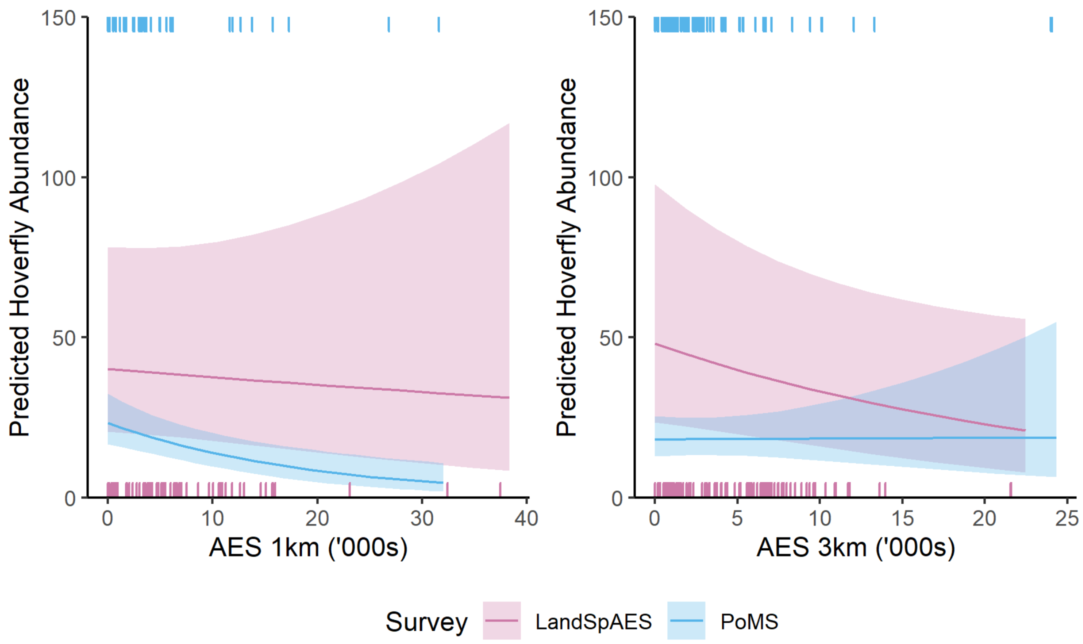

Figure 5.4.11. Predicted relationship between hoverfly abundance and local level (1km, left) and landscape level (3km, right) AES gradients for LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

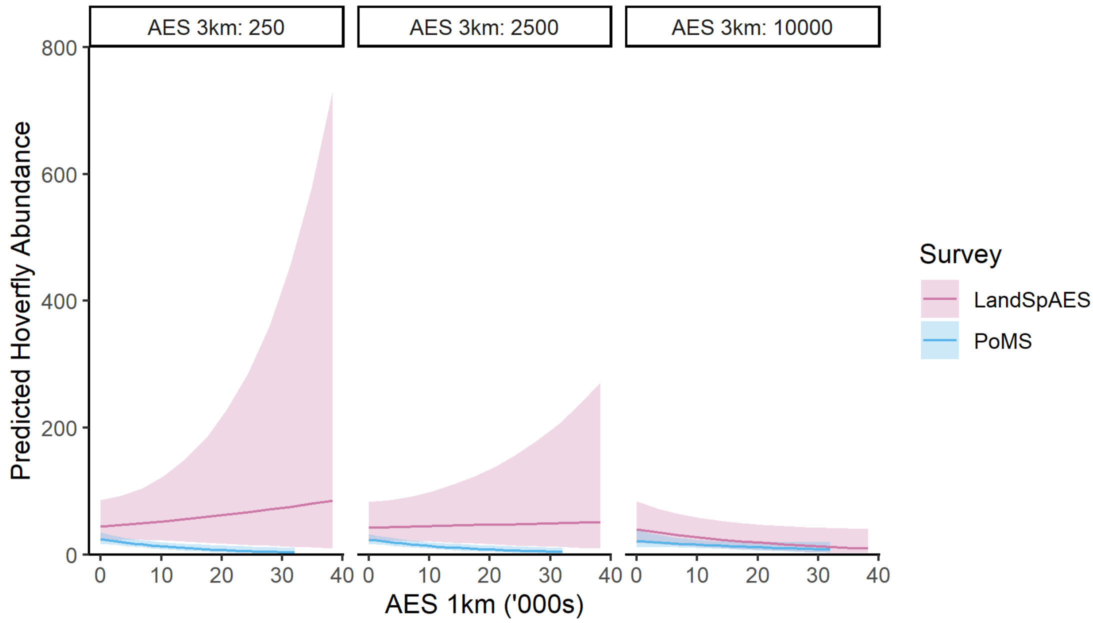

Figure 5.4.12. Predicted relationship between hoverfly abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for both LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction.

The difference between the local AES gradient effects was confirmed to be significant by the z test (Table 5.4.14), so again integrated modelling was not attempted for this hoverfly response variable.

Table 5.4.14. Z-test results for comparisons of AES coefficients between LandSpAES and PoMS for hoverfly abundance.

Comparison	1km AES	3km AES	Interaction
LandSpAES - PoMS	z = 2.325, *P* = 0.020	z = -0.776, *P* = 0.438	z = -1.774, *P* = 0.076

5.4.3.3. Discussion of hoverfly results

The hoverfly responses to the AES gradients showed strong differences between PoMS and LandSpAES, making it unfeasible to use any of the hoverfly responses for integrated modelling. For hoverflies, the main differences between the two datasets were in the local AES response, with PoMS data showing a strong negative response to local AES scores for hoverfly richness, diversity and abundance while LandSpAES data showed no significant response of AES gradients. At high landscape AES scores the PoMS and LandSpAES predictions of local AES effects were similar, though the interaction between the two AES gradients was not significant for any of the hoverfly response variables in either dataset.

The reasons for these negative relationships between hoverfly responses variables and AES gradients in the PoMS dataset would need further investigation, which is outside the scope of this project. Some hoverfly trait groups (e.g. hoverfly species with predatory larvae) can be linked to the area of arable land, and it is possible this or other habitat factors may be contributing to the patterns found in PoMS. Within the LandSpAES project, more detailed trait analyses of the data are planned once the field survey is complete, which would allow some of these possible relationships to be investigated.

5.4.4. Solitary bees

5.4.4.1. Explaining NCA variation

Using the PCA axes approach described in Section 4.2, we identified a number of axes which explained variation previously attributed to NCA for each response. Replacing NCA random effect with PCA axes did not change interpretation of the LandSpAES models, all AES parameters continued to be non-significant.

Table 5.4.15. Selected PCA axes for each response variable.

Response variable	**PCA axes selected**	
	LandSpAES	**PoMS**
Solitary bee richness	1, 2, 25, 28	1, 2
Solitary bee diversity	1, 2, 28	1, 2
Solitary bee abundance	1, 2, 13, 22	1, 2

5.4.4.2. Results of individual scheme models

5.4.4.2.1 Solitary bee species richness

For solitary bee species richness, we found differences in the relationships with local and landscape AES gradients between LandSpAES and PoMS, particularly in the effect of landscape AES. Both schemes showed a non-significant relationship with local AES, (Figure 5.4.13, left). However, LandSpAES showed a non-significant effect of landscape AES gradient while PoMS showed a significant negative landscape AES effect (Table 5.4.16, Figure 5.4.13, right). Neither PoMS nor LandSpAES showed any significant interaction effect between local and landscape AES (Figure 5.4.14).

All following prediction plots are standardized to be the prediction when 15 pan traps per year were used.

Table 5.4.16. Estimated relationships between solitary bee diversity and AES gradients for LandSpAES and PoMS. Estimated coefficients are shown ± standard error.

Survey	**Local (1km)**	***P***	**Landscape (3km)**	***P***	**Interaction**	***P***
LandSpAES	0.077 ± 0.047	0.101	-0.008 ± 0.03	0.790	-0.037 ± 0.043	0.389
PoMS	0.082 ± 0.058	0.160	-0.177 ± 0.071	0.013	0.04 ± 0.046	0.385

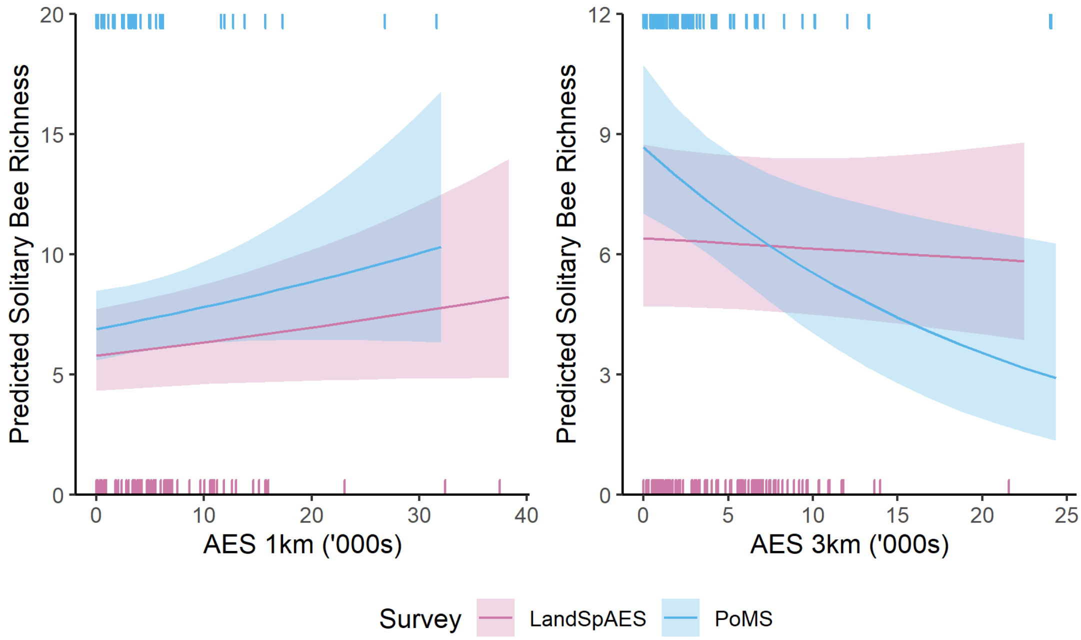

Figure 5.4.13. Predicted relationship between solitary bee richness and local level (1km, left) and landscape level (3km, right) AES gradients for LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

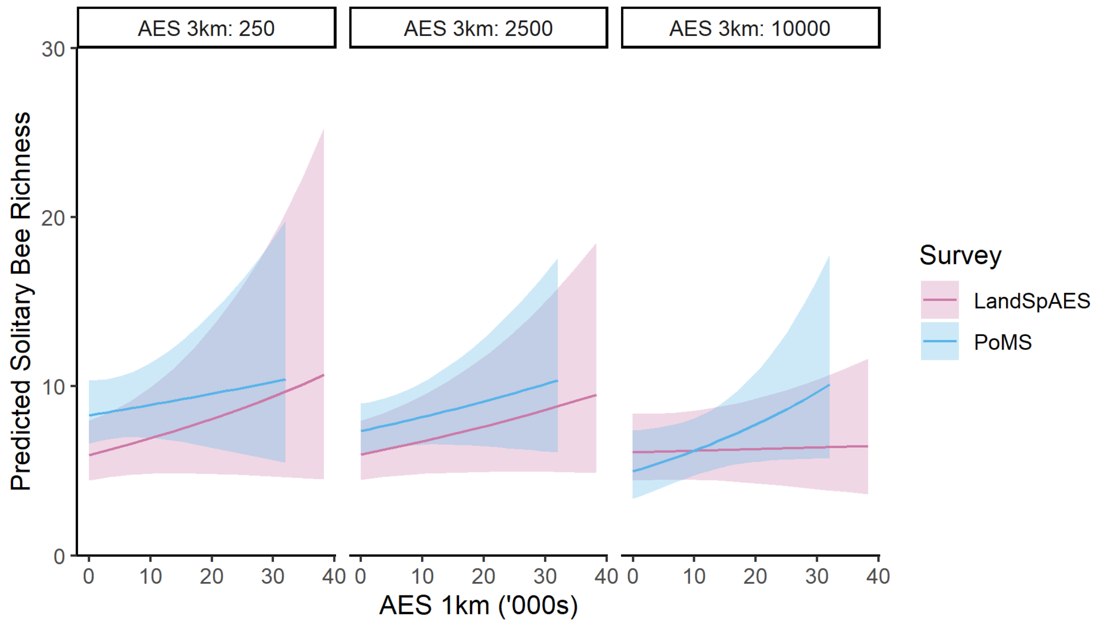

Figure 5.4.14. Predicted relationship between solitary bee species richness and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for both LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction.

The difference between the landscape AES gradient effects for PoMS and LandSpAES was confirmed to be significant by the z test (Table 5.4.17).

Table 5.4.17. Z-test results for comparisons of AES coefficients between LandSpAES and PoMS for solitary bee richness.

Comparison	1km AES	3km AES	Interaction
LandSpAES - PoMS	z = -0.066, *P* = 0.947	z = 2.180, *P* = 0.029	z = -1.223, *P* = 0.221

5.4.4.2.2. Solitary bee diversity

For solitary bee Shannon diversity we also found differences in the relationships with local and landscape AES gradients between LandSpAES and PoMS, again particularly in the effect of the landscape AES gradient. Both schemes showed a non-significant relationship with local AES, although PoMS showed a positive trend (Figure 5.4.15). However, LandSpAES showed a non-significant response to the landscape scale AES while PoMS showed a negative response to landscape AES (Table 5.4.18, Figure 5.4.15). Neither LandSpAES nor PoMS showed any significant interaction effect between local and landscape AES gradients (Figure 5.4.16).

Table 5.4.18. Estimated relationships between solitary bee diversity and AES gradients for LandSpAES and PoMS. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.036 ± 0.066	0.589	0.037 ± 0.038	0.326	-0.013 ± 0.057	0.826
PoMS	0.118 ± 0.063	0.066	-0.153 ± 0.067	0.024	0.028 ± 0.048	0.564

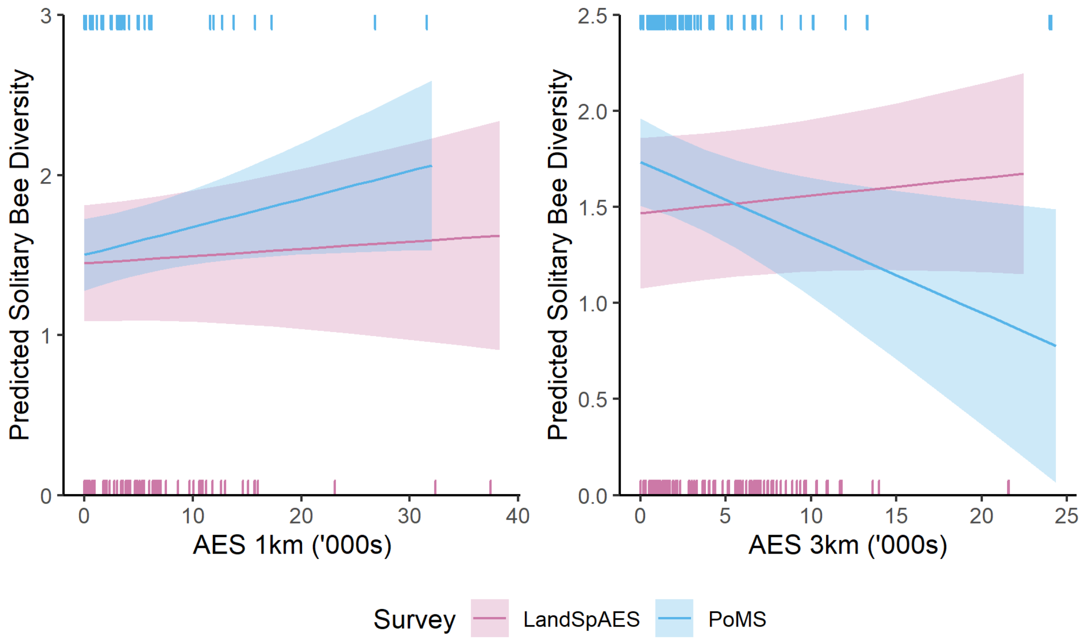

Figure 5.4.15. Predicted relationship between solitary bee Shannon diversity and local level (1km, left) and landscape level (3km, right) AES gradients for LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

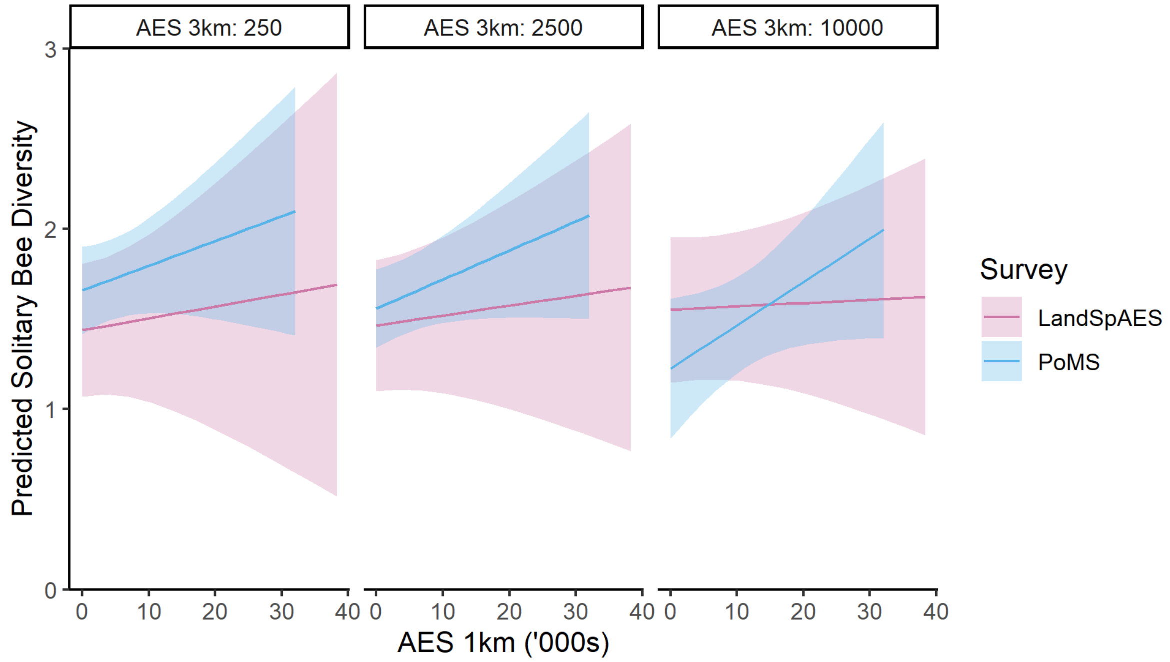

Figure 5.4.16. Predicted relationship between solitary bee Shannon diversity and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for both LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction.

The difference between the landscape AES gradient effects was confirmed to be significant by the z test (Table 5.4.19). Due to this difference, integrated modelling was not attempted for solitary bee diversity.

Table 5.4.19. Z-test results for comparisons of AES coefficients between LandSpAES and PoMS for solitary bee richness.

Comparison	**1km AES**	**3km AES**	**Interaction**
LandSpAES - PoMS	z = -0.893, *P* = 0.372	z = 2.488, *P* = 0.013	z = -0.542, *P* = 0.588

5.4.4.2.3. Solitary bee abundance

For solitary bee abundance, we found more similarities between the relationships with local and landscape AES gradients between LandSpAES and PoMS than for the other solitary bee response variables. Both datasets showed no significant relationship with local AES (Figure 5.4.17). However, both LandSpAES and PoMS showed a negative effect of the landscape level AES gradient, which was significant for PoMS but non-significant for LandSpAES (Table 5.4.20). Neither LandSpAES nor PoMS showed any significant interaction effect between the local and landscape AES gradients (Figure 5.4.18).

Table 5.4.20. Estimated relationships between solitary bee abundance and AES gradients for LandSpAES and PoMS. Estimated coefficients are shown ± standard error.

Survey	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.04 ± 0.101	0.691	-0.096 ± 0.062	0.120	0.066 ± 0.089	0.456
PoMS	0.029 ± 0.101	0.773	-0.264 ± 0.11	0.017	0.073 ± 0.077	0.342

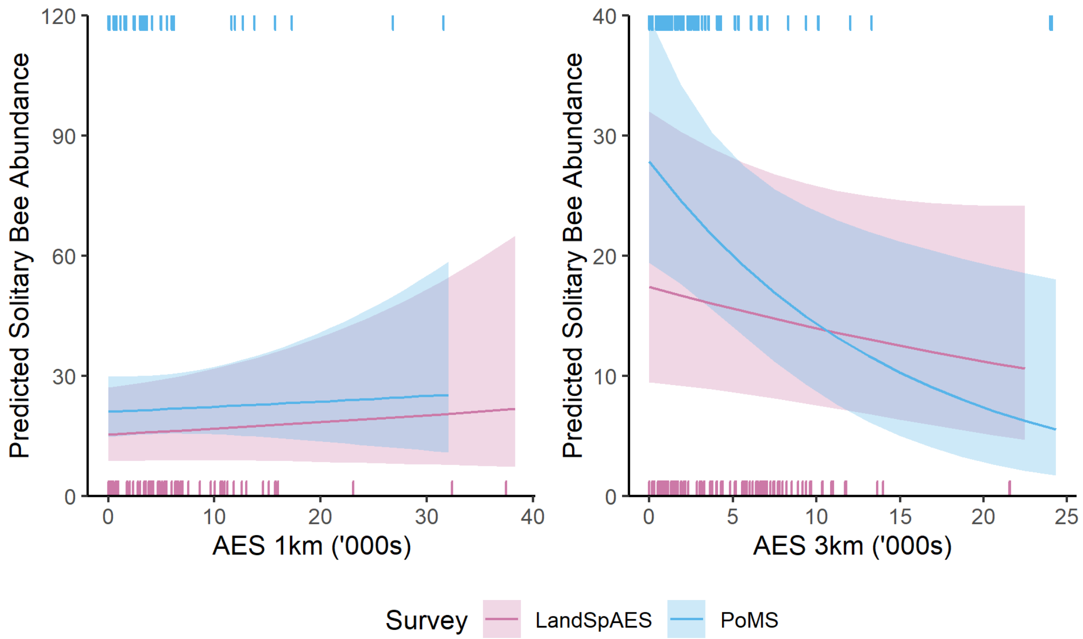

Figure 5.4.17. Predicted relationship between solitary bee abundance and local level (1km, left) and landscape level (3km, right) AES gradients for LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

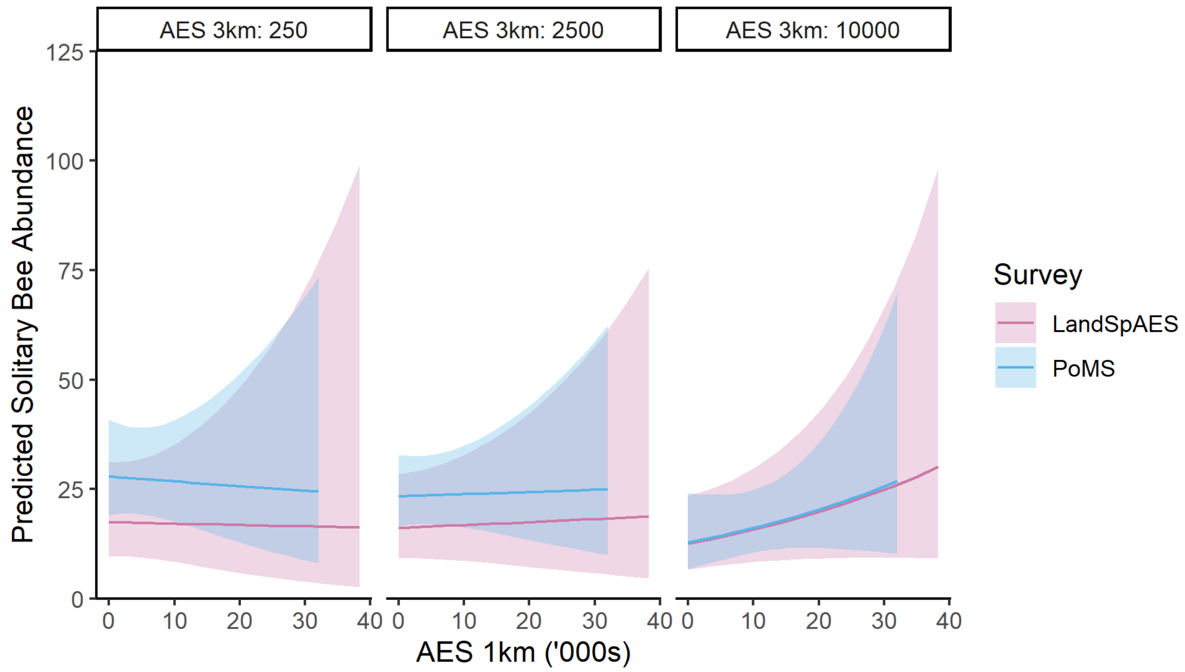

Figure 5.4.18. Predicted relationship between solitary bee abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for both LandSpAES and PoMS. Shaded areas indicate confidence intervals around the prediction.

The differences between the responses of solitary bee abundance to local, landscape AES gradients and their interaction across the two datasets was confirmed to be non-significant by the z test (Table 5.4.21).

Table 5.4.21. Z-test results for comparisons of AES coefficients between LandSpAES and PoMS for solitary bee richness.

Comparison	**1km AES**	**3km AES**	**Interaction**
LandSpAES - PoMS	z = 0.078, *P* = 0.938	z = 1.329, *P* = 0.184	z = -0.057, *P* = 0.955

5.4.4.3. Integrated models

Due to the differences in AES responses between PoMS and LandSpAES, integrated modelling was only attempted for one variable, solitary bee abundance.

5.4.4.3.1 Solitary bee abundance

To create an integrated model of solitary bee abundance including data from both LandSpAES and PoMS, we included a term to account for between scheme differences in mean solitary bee abundance. There was good evidence that slopes were similar between schemes and therefore a random effect for slope was not included.

An integrated model of solitary bee abundance provided similar inference as the LandSpAES and PoMS models, finding no significant relationships between solitary bee abundance and either local (1km) or landscape (3km) AES gradients, or the interaction between AES gradients (Table 5.4.22; Figures 5.4.19, 5.4.20).

Table 5.4.22. Estimated relationships between solitary bee abundance and AES gradients for LandSpAES and the integrated model. Estimated coefficients are shown ± standard error.

Model	Local (1km)	*P*	Landscape (3km)	*P*	Interaction	*P*
LandSpAES	0.040 ± 0.101	0.691	-0.096 ± 0.062	0.120	0.066 ± 0.089	0.456
Integrated	0.013 ± 0.080	0.8611	-0.062 ± 0.063	0.327	0.019 ± 0.054	0.731

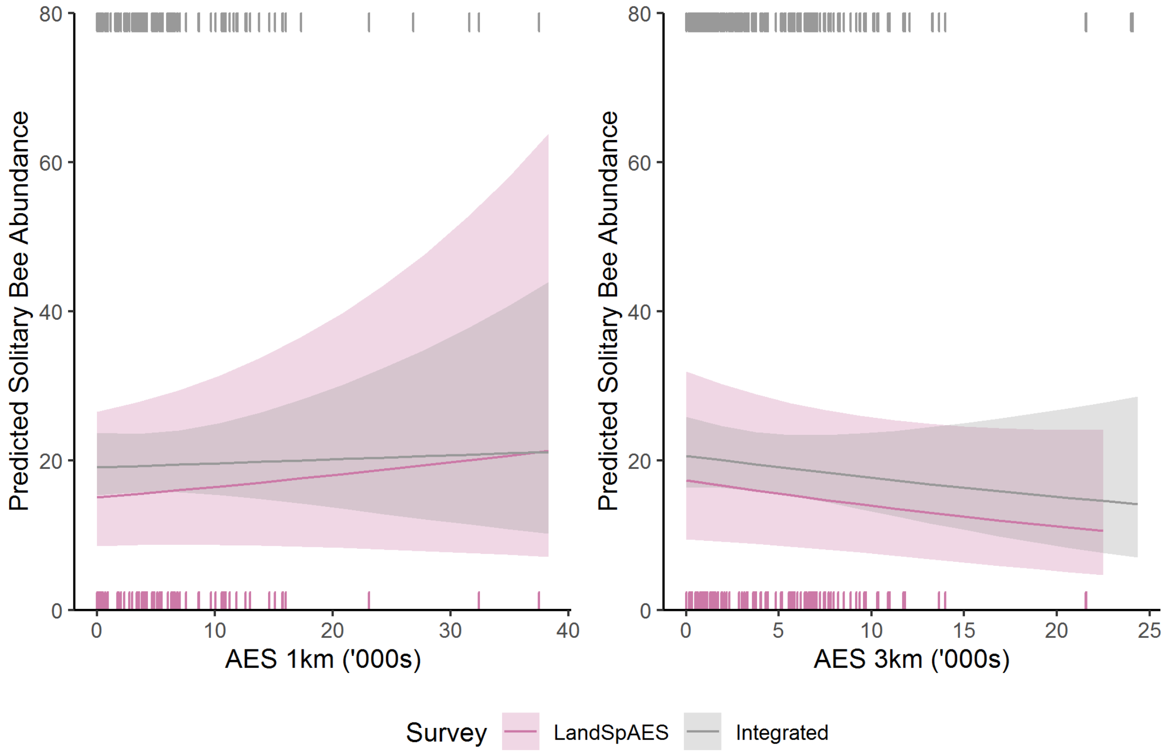

Figure 5.4.19. Comparison of predictions of solitary bee abundance in relation to local scale (1km) and landscape scale (3km) AES gradients from the LandSpAES data and integrated model. Shaded areas indicate confidence intervals around the prediction. Tick marks show the distribution of scheme data along the AES gradients.

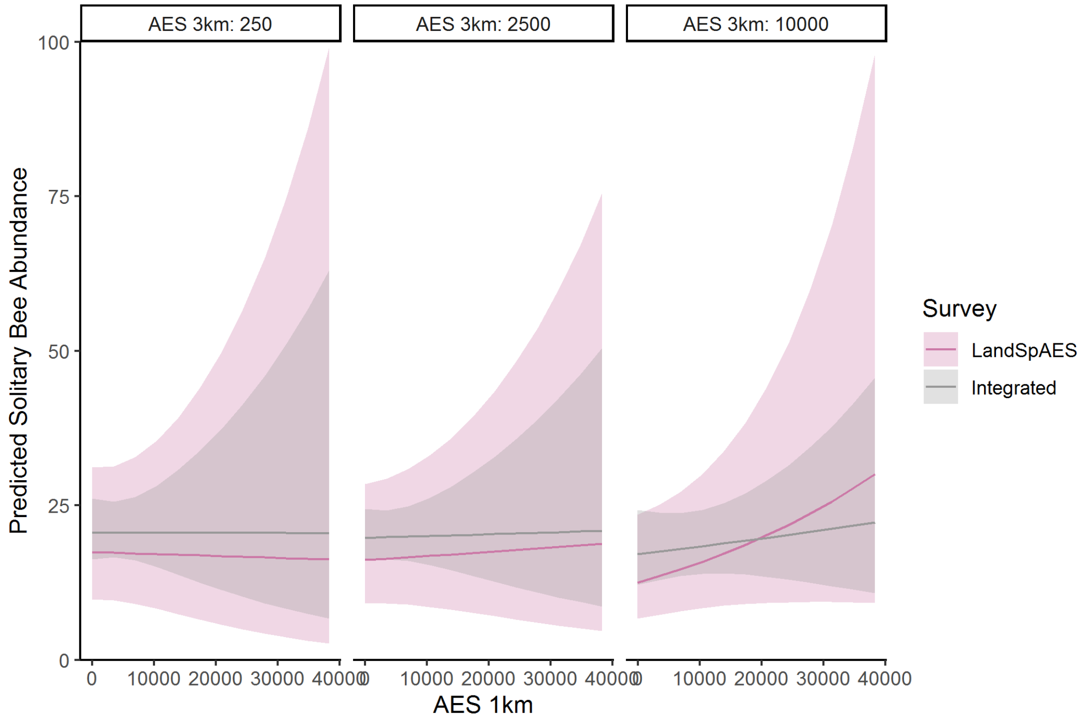

Figure 5.4.20. Predicted relationship between solitary bee abundance and local level (1km) AES gradient at different levels of landscape level (3km) AES gradient, demonstrating an interaction between local and landscape gradients. Interaction effects are shown for the LandSpAES model and integrated model. Shaded areas indicate confidence intervals around the prediction.

The integrated model demonstrated lower uncertainty in predicting solitary bee abundance than the LandSpAES model alone (Table 5.4.23), shown by lower MAE and RMSE. Coefficients of variation were similar. The reduced uncertainty can also be visualised in Figures 5.4.19 and 5.4.20 as narrower confidence intervals on predictions. The integrated model also estimated AES terms with higher precision shown by smaller standard errors on local (1km) and interaction terms in Table 5.4.22.

Table 5.4.23. Evaluation of integrated and LandSpAES models. RMSE = root mean square error, CV = coefficient of variation, MAE = median absolute error.

Model	**RMSE**	**CV**	**MAE**
LandSpAES	68.6	1.31	36.4
Integrated	39.4	1.31	17.9

5.4.4.4 Discussion of solitary bee results

Solitary bee species richness and diversity responded difference to the landscape AES gradient, with PoMS showing a negative response to landscape gradient, while LandSpAES data showing no significant responses. Solitary bee abundance was the only response variable from pan trap surveys that showed similar responses to local and landscape AES between LandSpAES and PoMS datasets. An integrated model fit to the LandSpAES and PoMS data showed reduced uncertainty around estimation of solitary bee abundance compared to either dataset alone, and no significant effects of the AES gradients at either scale.

5.4.5 Discussion of overall pan trap results

LandSpAES and the CitSci scheme PoMS showed differing responses to AES gradients for nearly all responses. There were no significant responses to AES gradients in any of the LandSpAES models, while PoMS showed some significant negative responses to AES gradients in some responses. These differences may be related to the small size of both datasets, the smaller number of visits within PoMS, the uneven coverage of the AES gradients within PoMS, and / or the low numbers of sites at the high end of the AES gradients in both the LandSpAES and PoMS datasets.

The scoping of the PoMS data (Section 3.2.5) showed some moderate correlations between the AES gradients and habitat variables. For example, both the local and landscape AES gradients were moderately negatively related to the area of arable land, and positively correlated to area of semi-natural habitat. The small number of survey sites for PoMS means it is possible that one or two survey squares are driving the correlations found between AES gradients and habitat variables. It is possible that the negative relationships found between the local AES gradient and the hoverfly response variables (and the landscape AES gradient and solitary bee species richness and diversity) are linked to relationships with other habitat variables, rather than being caused by the effects of AES gradients. However, further analyses of PoMS data would be needed to explore this further.

5.5 Summary of key results across citizen science schemes and LandSpAES

We found that it was possible to successfully replace the NCA random effect in LandSpAES models with fixed effects using PCA axis scores. Replacing the NCA random effect with PCA axes enables better exploration of AES gradient effects in areas surveyed under CitSci schemes, where ‘NCA effects’ are not known. Replacing the NCA effect reduced or had little change (ΔAIC < 5) in AIC, in all but one response where AIC increased by 14. This replacement caused only small changes in the estimated AES gradient effects in the LandSpAES data, and in most cases there was no change in inference compared to the provisional LandSpAES results (Section 1.4). For bird and butterfly responses, there were some cases where AES gradient effects that were not significant with the NCA random term, became significant after replacement with PCA axes in the LandSpAES data. It is important to note that the LandSpAES models used here are not a direct comparison to those previously reported due to updated option uptake data obtained for the landscape scale AES gradients (Section 1.4). In addition, all LandSpAES model results should be seen as provisional as a fourth year of survey data is still to be collected.

We found that taxa responses varied in similarity between LandSpAES and the different CitSci datasets. For some responses (e.g. butterfly richness) there was strong evidence of highly similar relationships between LandSpAES and CitSci schemes in relation to the AES gradients. For other responses (e.g. abundance of Red List birds) there was strong evidence of highly dissimilar relationships between the LandSpAES and CitSci datasets. The similarity in responses to AES gradients between LandSpAES and the CitSci datasets are discussed for each taxon in more detail at the end of each individual results section above (Section 5.1.5, 5.2.5, etc.).

Relationships were found to be similar enough to attempt modelling datasets jointly for nine out of 27 response variables, suggesting a majority of responses did not show similar relationships. However, the distribution of similar responses varied between taxonomic groups and survey method, with all butterfly and bumblebee (transect surveyed) responses being similar between the LandSpAES data and CitSci schemes. By contrast, only one out of nine tested insect response variables from pan trap data were found to be comparable between LandSpAES and PoMS, and none of the pan trap bumblebee responses were comparable.

Integrated models provided a consistent reduction in uncertainty (based on lower MAE and RMSE and similar CV) and showed a comparable response to that found on LandSpAES for five of nine response variables where integrated models were trialled (butterfly richness, butterfly abundance, bumblebee richness, bumblebee abundance, solitary bee abundance). For whitethroat and yellowhammer, although integrated models reduced uncertainty the resulting integrated model relationships were quite dissimilar to the original LandSpAES relationships, due to the high weight of BBS data. Integrated models were most suitable for reducing uncertainty in quantifying AES gradient effects on taxon responses where there was strong evidence of similar relationships between the LandSpAES and CitSci datasets.

For the five response variables where integrated models resulted in reduced uncertainty and showed a comparable response to that found in LandSpAES, significant main effects of one or both AES gradients were found using the integrated model for two of the response variables (butterfly richness and butterfly abundance). No significant relationships with the AES gradients were found using integrated models for the other three response variables.

6. Discussion

6.1 Discussion of key results and project objectives

To answer the question of whether taxon responses to the AES gradients, observed using the LandSpAES data collected in years 1-3, can be found more widely outside the regions surveyed on LandSpAES we assessed three questions in the work reported above:

1) Can addition of covariates account for environmental variation between survey squares in each dataset, to improve the comparability of AES gradient effects between LandSpAES and CitSci schemes?
2) Do the CitSci scheme datasets show similar relationships between taxa responses and the AES gradients, to those found with the LandSpAES data?
3) Can integrated approaches to combining datasets be used to jointly model CitSci and LandSpAES data, and does integrated modelling reduce uncertainty in quantifying the effects of AES gradients on taxa responses at a national scale across England?

To address the first question, we used ordination to convert environmental covariates into PCA axes. We found that adding these axes to the LandSpAES models improved the ability to apply these models more broadly, by replacing the 'NCA effect' with axis scores that can be obtained for any 1km square. For further detail of how the use of PCA axes altered model fit (AIC) and results, see Summary of key results (Section 5.5.).

In relation to the second question, we found that similarity in response to AES between LandSpAES and CitSci schemes varied between taxonomic groups and the survey methods used to collect the different datasets. Butterflies and bumblebee CitSci datasets showed greatest comparability with LandSpAES data. These CitSci schemes (BeeWalk, WCBS and UKBMS) all have reasonably comparable methodology to LandSpAES, which was a deliberate part of the design of LandSpAES monitoring protocols. For butterflies, there was greater evidence of similarity between LandSpAES and WCBS, both of which were designed to monitor 1km survey units, than between LandSpAES and UKBMS. UKBMS transects can extend outside of the focal 1km square unit and therefore it may be more difficult to link AES and PCA axis scores accurately to UKBMS observations. We were also unable to account for variation in transect length in UKBMS data in the timescale of this analysis, which may also explain differences in the relationships observed in this dataset. Notwithstanding these differences between the WCBS and UKBMS schemes, overall the majority of butterfly and bumblebee responses to AES gradients were quite similar in the LandSpAES dataset and at least one CitSci scheme dataset.

For insect responses calculated from pan trap data (for bumblebees, solitary bees and hoverflies), the majority of responses were not similar between LandSpAES and PoMS. This may be a function of the small size of the PoMS dataset in comparison to the other CitSci schemes. In addition, scoping of the PoMS dataset showed higher correlations between AES gradients and habitat variables than any of the other CitSci schemes used for the analytical work (Section 3.2.5). These moderate correlations may explain why some relationships observed in PoMS (e.g. a negative relationship between hoverfly richness and local AES) were not observed in LandSpAES where potential correlations between AES gradients and habitat were avoided in the design. Given the current small size of PoMS, which is a recently launched and expanding CitSci scheme, it may not currently be possible to disentangle the effects of the AES gradients and habitat variables on pollinator responses accurately within this CitSci scheme.

For birds, we found that the majority of responses to AES gradients were not similar between LandSpAES and BBS. Some significant relationships to AES that were observed in LandSpAES were not seen in BBS, and in some cases conflicting trends were observed (i.e. a positive effect in one dataset and a negative effect of AES in the other). The sample size in BBS was much greater than that for LandSpAES. Interestingly, despite larger sample sizes in BBS, there were some responses for which a significant relationship was observed in LandSpAES but not in the BBS. As discussed in the methods (Section 4.1), not all habitats or taxa surveyed by the BBS may be included in the much smaller LandSpAES dataset. Also, while the BBS data covers the whole range of the AES gradients, the local AES gradient, in particular, was dominated by BBS squares at the low end of the range of gradient values (Section 3.2.1). Relationships between bird responses and AES gradients in BBS may therefore be dominated by the large number of squares with low AES gradient values, whereas LandSpAES analyses sampled low to high AES values in a balanced design. Due to the much larger sample size in BBS, the integrated models were dominated by the BBS signal and had little similarity to the LandSpAES result, suggesting that these models may not be as helpful for extrapolation. The strongest evidence supporting integration for birds came from species-specific abundance models, probably because these variables are more sensitive, with spatially consistent relationships, to environmental variation such as AES score. However, even this only applied to two of the six species that were considered, so it is likely that they have sampled rather different elements of the variation in the environment, and integration appears not to be a strong approach for AES effect extrapolation for birds. The bird results emphasize the differences between a targeted monitoring project, like LandSpAES, which was designed to maximize power to detect AES gradient effects, and a CitSci scheme which was designed for the broader purpose of detecting changes in bird populations over the medium and long-term, and across the wider countryside.

Integrating LandSpAES with CitSci data has the potential to improve estimates of AES gradient effects at a national scale in two ways. Firstly, by extending the AES gradient ranges observed to higher values, and secondly by reducing uncertainty in modelled relationships. In exploring the third question above, we showed that integrated modelling of LandSpAES and CitSci data resulted in a reduction in uncertainty and comparable relationships to modelling LandSpAES data alone for five out of nine tested response variables. In general, integrated models had similar coefficients to the LandSpAES models but much lower uncertainty and included data from a more representative sample of England. However, for some responses integrated models provided no benefit, and in others they simply re-iterated a CitSci scheme that dominated the sample, suggesting that integration is not suitable in all cases.

For the five response variables where integrated models resulted in reduced uncertainty and showed a comparable response to that found on LandSpAES, significant main effects of one or both AES gradients were found using the integrated model for two of the response variables (butterfly richness and butterfly abundance). No significant AES gradient effects were found for the two bumblebee responses and solitary bee abundance, either in the integrated or the LandSpAES models.

6.2 Discussion of the analytical approaches explored in this project

This project demonstrates the value of the AES gradient scores developed in Staley *et al.* (2016), by showing that they can be used to find relationships across both the LandSpAES and the CitSci datasets. The AES gradients can be applied across all landscapes; this was demonstrated in the LandSpAES project, but has been confirmed in this project which shows that relationships observed in LandSpAES hold at the national scale for some taxa. These gradient scores may be a valuable tool to explore relationships with AES in other projects, and could be used to explore scenarios of future AES.

This project explored the potential for integrated modelling approaches to be used, in order to reduce uncertainty in extrapolation of LandSpAES results. We found that, where there was strong evidence of similar responses between LandSpAES and CitSci datasets, then we could include both in a single model. Integrated models tended to show increased precision around AES effects and in a majority of cases produced less uncertain models. Integrated models provided consistent results that are representative over the domain and the AES gradient, exploiting the benefits of the CitSci and LandSpAES data respectively. However, in some cases uncertainty was reduced only slightly or increased as a result of integration. This may be due to relationships in LandSpAES and CitSci being dissimilar enough that although statistical tests confirmed similarity of coefficients, integration does not reduce uncertainty (an example may be butterfly diversity). Increased uncertainty may also reflect differences between the datasets (e.g. in the survey design and protocols) that are not accurately captured by the models. We fitted relatively simple models in this project, and explored the potential to fit more complex models that would have allowed AES effects to differ between datasets in an integrated model. In most instances these more complex models failed to converge adequately.

One issue with integrated models, as observed for the bird responses, is that a larger dataset will outweigh a smaller in the integrated model. BBS is a very large dataset compared to LandSpAES, and therefore the estimated relationship with AES in the integrated model was dominated by the relationship observed in BBS. Approaches to weight data to account for differences in size could be explored in the future.

6.3 Comparisons with ongoing work on the LandSpAES project

The LandSpAES field survey is ongoing, and these results are based on data from the first three years of survey. Therefore, results presented here from the LandSpAES data should be seen as provisional and subject to change. We have also made some changes to the LandSpAES models from the main project, notably to update the landscape AES scores using new option data. This has impacted the range of landscape AES gradient scores covered by the LandSpAES survey squares. LandSpAES analyses conducted once the ongoing fourth year of field survey is complete will use these updated landscape AES gradient scores.

The main LandSpAES project will include analysis of a wider range of trait groups for insects once the survey is complete. Provisional analyses have shown some insect trait groups may respond to the AES gradients even when the whole taxon does not (e.g. abundance of mid-tongue length bumblebees vs. abundance of all bumblebees). Insect trait groupings will include larval and adult broad feeding group, mobility, degree of specialization and conservation status. Results from these final analyses will enable a more detailed understanding of the relationships between the ecology of insect species grouped by trait, and the AES gradients. In addition, final analyses of LandSpAES data will include multiple individual bird species, which may be more sensitive to variation in environmental predictors than the assemblage-level combined data, and may consider other options for modelling the data, such as zero-inflated Poisson models, which might fit the data structure for some species better.

Finally, the LandSpAES project includes surveys of taxa that were not included in the analytical work developed for the current project. Detailed moth surveys are being conducted on LandSpAES, but moth response variables are not included in this modelling work, as the scoping indicated too many differences between the LandSpAES moth survey and the potential moth CitSci scheme, as well as strong correlations between the two AES gradients in the moth CitSci data (Section 3.2.6). Bats are also being surveyed on LandSpAES, but there was no suitable national CitSci scheme for bats that could be included in the scoping for the current project.

6.4 Potential for additional analytical work

Much of the work on the current project has gone into collating the data, calculation of the AES gradients for each 1km grid square in England, scoping the datasets, investigating the selection of environmental variables, and determining the analytical approaches for each stage of the modelling work. A substantial amount of time has gone into this development of the methods used here, at a stage when results from the ongoing LandSpAES baseline survey are provisional. Therefore, subject to availability of resources, there may be potential to apply the methods developed here to compare results from the CitSci data with the final LandSpAES baseline results, which would enable the method development work to be utilized again. In addition, there is the potential to apply these methods to a greater range of taxon response variables, for more detailed analyses of taxa trait groupings or species responses once year 4 LandSpAES data are available.

It might also be possible to re-do the analyses of BBS data, using a subsample of BBS squares that are selected to more evenly respresent the AES gradient ranges, using a weighted random process. However, as the differing results between models applied to BBS and LandSpAES data may be due to factors related to sampling coverage and methodological variation (see Section 5.1.5 and 6.1 for details), there is no guarantee this potential additional work would facilitate the use of integrated modelling for bird response variables.

In the longer term, the aim is to resurvey the LandSpAES sites to investigate the effects of AES gradients on temporal change in taxon and species responses. All the CitSci schemes included here are ongoing, so there might be potential to revisit this analytical work to also explore the use of integrated modelling for temporal response variables.

6.5 Conclusion

The broad aim of this project, which was to explore whether the provisional taxa responses to AES gradients found in the LandSpAES project could be detected at national scales using CitSci scheme data, was met. The successful joint modelling and reduced uncertainty for five response variables provides evidence that some AES gradient effects observed in the LandSpAES project can be reliably modelled at a national scale. However, this was true for only a minority of responses and there was considerable variation between the taxonomic groups and the CitSci schemes, in relation to whether the LandSpAES and CitSci datasets showed similar relationships between taxon responses and the AES gradients. This variation may be due to differences between the CitSci schemes in terms of size, design or distribution along the AES gradients. For the majority of response variables, integrated modelling was either not used due to the dissimilarity between datasets in relationships with AES gradients, or did not result in both reduced uncertainty and comparable relationships to modelling LandSpAES data alone. This shows that the ability to use these methods and datasets to explore relationships between taxon responses and AES gradients at a national scale is highly context-dependent, and that CitSci schemes cannot be assumed to provide equivalent inference to a specifically designed study.

Acknowledgements

This study was funded by Natural England (project LM04109) and we thank Susanna Philips, Rachel Sykes, Phil Grice, Ben Payne and James Phillips (NE), and Jordan Pinder and Sam Flint (Defra), for their input and advice.

Thank you to the Citizen Science monitoring scheme coordinators who provided data for this work. The analyses reported here contain data from the following monitoring schemes:

1) Breeding Bird Survey (BBS) is funded by a partnership of BTO, JNCC and RSPB, https://www.bto.org/our-science/projects/bbs.
2) UK Butterfly Monitoring Scheme (UKBMS) and Wider Countryside Butterfly Survey (WCBS) data © copyright and database right Butterfly Conservation, the UK Centre for Ecology and Hydrology, British Trust for Ornithology, and the Joint Nature Conservation Committee, (2021), https://www.ukbms.org.
3) UK Pollinator Monitoring Scheme (UKPoMS) data © copyright and database right Pollinator Monitoring and Research Partnership, https://www.ceh.ac.uk/our-science/projects/pollinator-monitoring.
4) BeeWalk data © copyright and database right Bumblebee Conservation Trust, (2021), https://www.beewalk.org.uk/.
5) Rothamsted Insect Survey moth trap locations were kindly provided by Chris Shortall at Rothamsted Research (https://www.rothamsted.ac.uk/insect-survey).

In addition, the analyses contain data from the Landscape-scale species monitoring of agri-environment schemes project (LM0465), funded by Natural England, https://www.ceh.ac.uk/our-science/projects/landspaes. This report also contains data from British Geological Survey materials ©NERC [2021]. Climate hydrology and ecology research support system meteorology dataset for Great Britain (1961-2017) [CHESS-met] data licensed from UK Centre for Ecology & Hydrology. © Database Right/Copyright UK Centre for Ecology & Hydrology. All rights reserved. Contains material based on Met Éireann data © Met Éireann, Met Office and OS data © Crown copyright and database right 2017 and University of East Anglia Climatic Research Unit © CRU

Thank you to all the landowners who have granted access for these surveys, and all the professional and volunteer surveyors who collected all the field data for the LandSpAES and CitSci scheme datasets analysed here.

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