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RESEARCH ARTICLE

Model-based assessment of the impact of agri-environment scheme options and short-term climate change on plant biodiversity in temperate grasslands

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Abstract

1. Agri-environment schemes (AES) incentivise land-management practices aimed at mitigating environmental impacts. However, their effectiveness depends on the duration and type of management. We modelled the potential for grassland AES options in Wales (UK) to achieve positive changes in plant diversity via change in soil conditions.
2. We modelled the response of plants and soils to the predicted effects of AES options over a 13-year time interval. We applied scenarios of change in soil conditions in three managed grassland types, using high-resolution baseline soil and vegetation data collected in grasslands across Wales, UK. We also applied scenarios of climate change to determine the extent to which this might modify the impact of AES intervention on plant species compositional turnover.
3. Empirical models of soil response to extensification were constructed from published experimental data and used to drive change in soil inputs to a small ensemble of ecological niche models for British plants. These models were applied to the local pool of species in each baseline (2 × 2 m) quadrat plus a wider 10 × 10 km pool from which we draw species absent at baseline but predicted to find conditions suitable as a result of AES intervention and climate change, thus estimating dark diversity at each location. Outputs were summarised by grouping species by the ecosystem functions and services they support and by matching projected species composition to the UK National Vegetation Classification.
4. Scenario modelling indicated that at least 10 years of management under grassland AES options were needed to achieve conditions suitable for desirable plant assemblages more typical of lower fertility habitats.
5. *Synthesis and applications*: We predict that management effects will have a more marked effect on vegetation and soil than predicted climate variation up to 2029. Realising modelled changes in habitat suitability as species compositional

turnover and community assembly is likely to require additional measures to assist plant dispersal and establishment.

KEYWORDS
climate change, dark diversity, ecological niche modelling, ecosystem services, functional diversity, plant species, soil quality, sustainable land management, sustainable resource management

1 | INTRODUCTION

Since the mid-1980s, agri-environment schemes (AES) have provided a mechanism whereby land managers are paid to reduce the intensity of agricultural management and its negative impacts on ecosystems while restoring and maintaining biodiversity (we term this extensification). However, doubt has been cast on the effectiveness of AES in delivering desired outcomes (Kleijn & Sutherland, 2003; Norton et al., 2014). Evidence of AES success is mixed and dependent on factors such as starting conditions, focal organism(s), focal habitat, desired public good and the length and intensity of management duration and monitoring (Critchley et al., 2004; MacDonald et al., 2019). While positive outcomes have been found in differing taxa and habitats (Bright et al., 2015; Dadam & Siriwardena, 2019; Keenleyside et al., 2011; MacDonald et al., 2019), others have reported (a) low success (i.e. maintaining the *status quo*); (b) inconclusive effects or (c) lack of sufficient monitoring (Arnott et al., 2018; Critchley et al., 2004; Davey et al., 2010; Kleijn & Sutherland, 2003; Mountford & Smart, 2014; Norton et al., 2014; Staley et al., 2018). Estimating the impact of future AES remains critical if they are to help address climate change and the biodiversity crisis cost-effectively (European Commission, 2013; Keenleyside et al., 2011; Pe'er et al., 2019; Rose, 2011). Previous evidence has shown that positive effects may take longer to observe than the typical length of AES monitoring (Maskell et al., 2014; Norton et al., 2014).

Determining AES success for plants and soils is of particular interest within the study area (Wales, UK). The Welsh Glastir scheme funds management interventions some of which are designed to restore soil conditions and plant species composition associated with habitats that have declined as a result of intensive land use (Rose, 2011; Welsh Government, 2016). Recent research in the United Kingdom has often focused on AES effects on more mobile taxonomic groups, for example, birds (Bright et al., 2015; Dadam & Siriwardena, 2019; MacDonald et al., 2019). Outcomes varied by taxa and habitat although more targeted AES interventions appear to have been more successful (Bright et al., 2015; Colhoun et al., 2017). Plants and soils, however, have been less studied in recent times with past research finding mixed success even over time periods beyond standard AES agreement times (Critchley et al., 2004; Feehan et al., 2005; Taylor & Morecroft, 2009). We focus on AES performance in temperate grasslands since these are a major focus for both food production and conservation of biodiversity (Simons & Weisser, 2017). The effects of extensifying management in grasslands vary in detectability and magnitude from short term; 3–5 years (Defra, 2015; Maskell et al., 2014) to long term; 10–30 years (Critchley et al., 2004; Pywell et al., 1994; Smith et al., 2014). These studies demonstrate that greater levels of restoration are achieved over longer time-scales. Thus, understanding the time-scale of soil and plant community responses to management is important to manage expectations among practitioners and policymakers. If restoration goals are likely to take longer to achieve than typical AES agreements then both monitoring and management are required over a longer period. Over more distant time horizons, it becomes important to know if ecosystem management outcomes could be altered by climate change (Díaz et al., 2020; IPCC, 2018). Here we explore if climate change is likely to risk delivery of benefits from future AES. This is important because plant species that might be expected to thrive under extensifying AES management could experience reduced habitat suitability if the local climate becomes increasingly unfavourable. The evidence for climate change impacts on plant species is somewhat species-specific and scale-dependent. A Europe-wide assessment suggests that over a time horizon extending to 2100, the United Kingdom will see lower (*c*. 10%) species compositional turnover than the Mediterranean zone (Alkemade et al., 2011) and overall net positive impacts on habitat suitability for a representative range of plant species by 2050 (Wamelink et al., 2020). A UK-centred assessment also estimated that around 40% of vascular plants had medium to high opportunity for expansion reflecting the northern range edge of many species in southern Britain while montane and northerly distributed species would retract (Pearce-Higgins et al., 2017). These studies assessed distributional change in suitability across large grid squares—typically 10 × 10 km. Yet these patterns are inevitably the upscaled and cumulative outcome of dispersal, establishment and population growth interacting with other species at the smaller scale of the vegetation patches within larger grid squares (Huston, 1999). Evidence for annual and longer-term effects of weather at this finer scale suggests that warmer, wetter conditions favour perennial grass species at the expense of smaller forbs (Dunnett et al., 1998; Silvertown et al., 1994). However, in a study of the drivers of vegetation change across low-productivity, semi-natural habitats in Scotland from the 1970s to 2005, Britton et al. (2017) detected positive climate impacts on patch-scale diversity of several plant species groups. Warmer but wetter future conditions could therefore interact with high residual fertility and filter against dispersal and establishment of species typical of less intensively managed grasslands. If this were to happen then any broadly positive effects of a warming climate are unlikely to be realised without field and landscape-scale management intervention (Grass et al., 2021). In this respect, longer-term outcomes are likely to be critically dependent on the interplay between subsidised extensification, for example, via AES, and other socio-economically driven changes in land use and their potential to create or reduce the conditions necessary for dispersal, establishment and persistence within and across the habitat matrix as the climate changes (Di Marco et al., 2019; Grass et al., 2021).

Determining the success of AES in achieving ecological goals depends on defining change in terms of appropriate indicators and modelling future progress towards or away from ecological end-points (Horrocks et al., 2014). We use this approach coupled with simple plant species ecological niche models (ENMs) to forecast impacts on plants and soils in the presence of climate change. We estimate impacts at fine resolution but at a national scale across Wales, UK (Emmett & the GMEP team, 2017). We model local and dark diversity (Pärtel et al., 2011). This comprises species observed in each baseline location and therefore assumed to be suited to conditions prior to applying scenarios of climate and management change. This is the 'local' pool. We also allow for species-compositional turnover in response to these scenarios by modelling plant species absent from the baseline but present in the wider 10×10 km species pool around each baseline location. This is an estimate of 'dark' diversity, that is those species that are absent from the baseline but predicted to find conditions favourable given AES intervention and climate change. These additional species may end up more suited to the conditions at each modelled location than the observed 'local' pool as conditions change. Modelling local and dark diversity, therefore, indicates the ecological restoration potential around each location.

We forecast impacts on plants and soils using the MultiMOVE R package (Henrys et al., 2015; Smart et al., 2010). Inputs to the model are vegetation height, indicators of soil conditions and climate variables. We change the baseline values of these inputs over the relatively short interval, 2016 to 2029, to explore near-term impacts of AES management with and without predicted climate change. The result is a suite of forecasts that estimate the impact of scenarios of climate change and management impact on plant species composition over time.

In summary, we address the following research questions: (1) Does extensified management over a maximum interval of 13 years increase the suitability of conditions for species that support ecosystem functions and services (nitrogen fixers, nectar plants, forage grasses, injurious weeds—an ecosystem dis-service to agricultural production) as well as promoting beneficial change in soil conditions? (2) What impact will climate change have and could it offset gains linked to AES intervention?

2 | MATERIALS AND METHODS

2.1 | Data sources

Soil and vegetation data were recorded from 2×2 m square quadrats (n=828 nested in 300 1 km squares) located across Wales as part of the Glastir Monitoring and Evaluation Programme (GMEP)

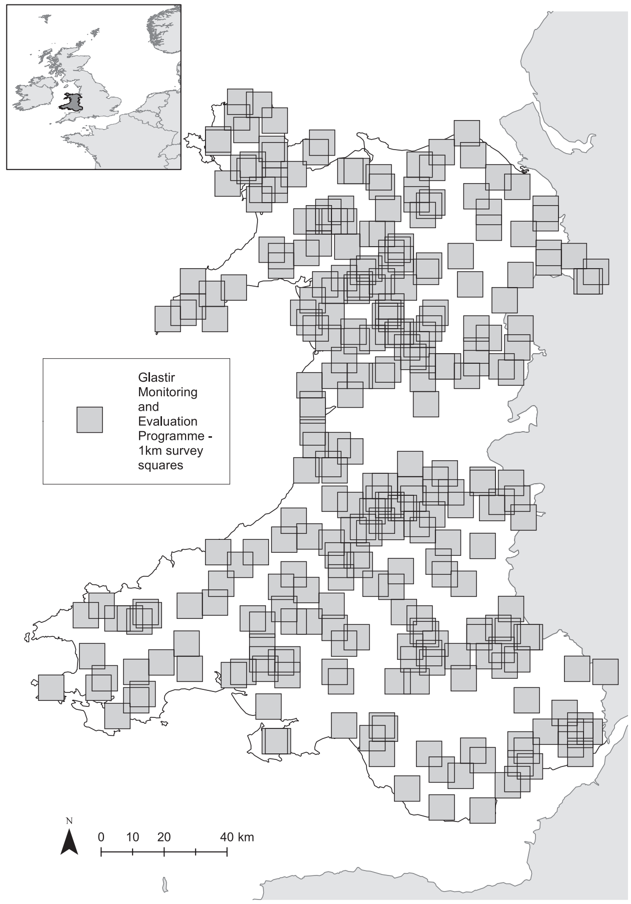

FIGURE 1 Map of the Glastir Monitoring and Evaluation Programme (GMEP) 1 km squares surveyed between 2013 and 2016, survey squares are not shown to scale to preserve the confidentiality of their locations.

survey carried out between 2013 and 2016 with each quadrat recorded once over that time (Figure 1). See Emmett and the GMEP team (2017) and Seaton et al. (2020) for detailed soil and vegetation sampling methods. Soil samples were taken from one corner of each 2×2 m quadrat to determine gravimetric % soil moisture; fresh pH in distilled water, total C% and total N%. The GMEP soil and vegetation data were collected using a random design stratified by a physiographic classification of all 1 km squares across Wales. We focus on three grassland habitat types targeted for extensification within AES; improved (IG), neutral (NG) and acid grassland (AG) as defined in Jackson (2000), see Supplementary Material 1.

2.2 | Species ecological niche modelling

We used the MultiMOVE R package (Henrys et al., 2015) as the source of ENMs for higher and lower plants in the British flora. The package has been tested and applied in a number of studies under a range of contrasting scenarios (De Vries et al., 2010; Emmett & the GMEP team, 2017; Henrys et al., 2015; Rowe et al., 2015; Smart et al., 2019). In summary, it uses a small ensemble of five statistical methods to model the realised niche of 1262 taxa covering the most common and many less common plants and bryophytes (Henrys et al., 2015; Smart et al., 2019 for full description) in the British flora. Since the majority of dominant and frequent species in the flora are included, the models are able to account for plants that contribute the most to supporting ecosystem functions and services across British ecosystems. There are seven inputs to each model for each species; the three mean Ellenberg indicator values that equate with pH (Ellenberg R), soil moisture (F) and fertility (N), cover-weighted vegetation height and three climate variables. The derivation of these inputs is described below.

The mean Ellenberg values represent plant species preferences along environmental axes (Ellenberg et al., 1992). Using mean Ellenberg scores calculated from the species composition of each training plot as model inputs allowed every plot to contribute to model building, with the proviso that the species being modelled was removed from the calculation of each mean Ellenberg score to avoid circularity. Along with cover-weighted vegetation height and the three climate variables, these indices quantify the realised niche of each species as represented in the national-scale, fine-resolution presence–absence data used to train the models (Henrys et al., 2015; Smart et al., 2010). When used in predictive mode the habitat suitability of a species is projected into the ecological space defined by the model inputs at baseline and then given a scenario of climate and management change the model inputs are adjusted and the model run again. Thus, the predicted position of a species can change in this suitability space as its model inputs change.

2.3 | Soil change models

An additional suite of models was used to quantify how soil conditions would be likely to change in response to AES management options in grassland. A literature search was conducted to assemble data on how soil carbon, nitrogen and pH changed over time with management applied to British grassland habitats. Studies were only included where soil analysis methods matched those used in GMEP and where the treatment effect was a reasonable match to AES options (Table 1). This search resulted in datasets of varying sizes for each variable. Requests were made to study authors to provide full datasets, including relevant open-access data. See Supplementary Material 4, for contributing datasets and selection methodology.

Generalised linear mixed-effect models (LMER4 R package; Bates et al., 2015) were constructed to estimate the change in each soil variable over time given each extensification scenario (Table 1). Details for the categories for each scenario are in Supplementary Material 4.

Soils across Britain are recovering gradually from historically high sulphur deposition (Emmett, 2010; Kirk et al., 2010). We accounted for this by adding a pH annual increment calculated from 29 years of data for each grassland habitat type (Emmett, 2010).

2.4 | Deriving Ellenberg scores from soils data

An additional modelling step was necessary to be able to predict changes in habitat suitability from changes in measured soil conditions. This step involved building statistical models of the relationship between soil variables and the mean Ellenberg values calculated from the plant species composition of the training data used to build MultiMOVE. However, while every quadrat in the training data could be used to calculate mean Ellenberg values, only 5% of the training data had measured soil variables (Henrys et al., 2015; Smart et al., 2019). Therefore, relationships were derived between mean Ellenberg scores and the measured soil variables just in the subset of data that had both kinds of data. This resulted in transfer functions that could be used to convert measured or modelled soil variables into the required Ellenberg scores used as MultiMOVE inputs. The transfer functions were generated using neural network models (see Supplementary Material 3). This method was selected because of the need to optimise accuracy based on a small set of predictors with strong prior ecological justification for their inclusion. Model construction was achieved using the neural

TABLE 1 Scenario descriptions for the agri-environment scheme management prescriptions modelled. Two climate states were applied both from UKCP18 temperature and precipitation climate change predictions available at 1 × 1 km resolution: High emissions (RCP 8.5 predictions 'worst case scenario'); and Baseline average climate (1981–2016). Full scenario details and soil variable modelling details can be found in Supplementary Material 4: Table 1B. Recovery from acidification refers to a soil pH increment being applied each year consistent with the effect of reduced sulphur deposition in the last 50 years across the United Kingdom.

Scenario	Management description	Recovery from acidification applied
Baseline	Observations from the GMEP field survey	No
Low inputs (LI)	Management using a reduced amount of fertiliser application with sward height managed to promote plant diversity. Medium intensity, minimal fertiliser inputs and intermittent grazing	Yes
Reduced stocking	Grassland with a reduced number of livestock with sward height managed to promote plant diversity. Medium intensity management with intermittent grazing and cutting	Yes
No inputs	No chemical inputs applied. Extensification management with intermittent grazing and cutting with minimal to no fertiliser applications	Yes

network R package (Venables & Ripley, 2002) and is described in Supplementary Material 3.

2.5 | Calculating cover-weighted vegetation height

Cover-weighted canopy height is another model input variable. It expresses the successional stage of the vegetation (Henrys et al., 2015; Smart et al., 2010) and is calculated as follows across the $i=1$ to n species in each sample plot:

$$\text{Cover weighted canopy height} = \frac{\sum_{i=1}^{n}(\text{vegetative canopy height} \times \text{cover})}{\sum_{i=1}^{n}(\text{cover})}.$$

The species % cover was recorded in each plot while average canopy height data were obtained from published sources (Hill et al., 2004; Stace, 1997).

2.6 | Climatic data

Three climatic variables (minimum January and maximum July temperature and total annual precipitation) are also used as inputs to MultiMOVE. Long-term annual average values of these variables were originally used to train the MultiMOVE models and are used as inputs in predictive mode (Henrys et al., 2015; Smart et al., 2010). The UKCP18 database (Lowe et al., 2018; Met Office, 2019) was used as the source of all climate data. The historical climate was derived from UK land surface observations (HadUK-Grid) interpolated from meteorological station data onto a uniform 1 km grid (Lowe et al., 2018; Met Office, 2019). The observed data were averaged from 1981 to 2016 to give a baseline representative of conditions in 2016. For future high emissions (RCP8.5), climate projected from UKCP18 was selected and downscaled to 1×1 km matching the baseline resolution. This represents a worst-case scenario projected climate (Robinson et al., 2022). This approach interpolates variables to a finer resolution while adjusting for local topography (Supplementary Material 2 & Robinson et al., 2022).

2.7 | Defining the plant species pool and modelling dark diversity

We modelled a species pool that combined the list of species observed in each baseline GMEP quadrat with additional species recorded in the wider 10 km square grid cell in the last 20 years (BSBI, 2018; Walker et al., 2010). In so doing we allow the estimated species composition of each plot location to change because modelling can draw on this wider pool. That is, given a scenario of management and climate change the plant species with the highest modelled habitat suitability values could all have been absent from the baseline species composition in each plot. This amounts to modelling dark diversity (Pärtel et al., 2011) change where we include species that are estimated to find conditions suitable at a location even when absent at baseline. This is possible to do with high spatial realism because of the high quality of both regional species pool data available for Britain (BSBI, 2018; Walker et al., 2010), and the availability of high-resolution soil and plant observations at each modelled location (see Section 2.1).

2.8 | Model testing

To build confidence in model application, we tested whether predicted habitat suitability scores for each baseline GMEP plot correlated with the observed species' presence. We used logistic regression with modelled habitat suitability as the sole explanatory variable. A two-tailed Wilcoxon rank test was also applied to test whether species absent in the observed baseline data had significantly different statistical ranks to species that were present. All analyses were conducted in the R environment (R Core Team, 2019).

2.9 | Scenario modelling

The modelled baseline represents the observed environmental and climatic conditions in 2016. We then defined scenarios of change in the model inputs (soil conditions and vegetation height) representing the impact of AES interventions over 5, 10 and 13 years. The interventions were all based on extensifying options in the Welsh Glastir AES that reduce fertiliser inputs and reduce stocking rate to achieve a target vegetation height. See Supplementary Material 4: Table 1B.

Three scenarios were defined—reduced stocking (RS), low soil nutrient inputs (LI) and no inputs (NI) (Table 1). The soil models generated above from the experimental literature estimate change in soil variables given the assumed impact of the Glastir AES options (see Supplementary Material 4: Table 1B). This means we can use the soil models to predict the amount of change in the soil variables expected over the different time periods and then use these as inputs to the ENM after first converting them into mean Ellenberg scores using the neural network models (see Section 2.3). The scenarios were created by using empirical models of management-induced change in soil variables to represent the impact of relevant AES options, details in Table 1. See above and Supplementary Material 4.

2.10 | Summarising ecological niche model outputs

The predictions at baseline and in response to each scenario were summarised in two ways. First by treating the output habitat suitability scores for each species in each plot as a % frequency, this profile of modelled outputs for each plot was matched to the British National Vegetation Classification (NVC; Rodwell, 1998) using the MAVIS software (Smart, 2000). Second, the modelled suitability scores for species classified by particular ecosystem-service supporting groups were summed to give an estimated species count per group per 2×2m quadrat for that functional group (Calabrese et al., 2014). The species groups used were as follows: nitrogen-fixers (nutrient cycling); nectar plants (pollinator food source; Baude et al., 2016); forage grasses (livestock production) and injurious weeds (Maskell, Henrys, et al., 2020) of which increased abundance can be viewed as a disservice to agricultural production (Smart et al., 2017). See Supplementary Material 5: Table 3 for species lists.

3 | RESULTS

3.1 | Testing the model against baseline observations

Greater modelled suitability scores were associated with a greater chance of the modelled species being present in a quadrat. Plant species observed in each quadrat also had a significantly higher rank suitability score ($p < 0.001$; two-tailed Wilcoxon rank test, see Supplementary Material 5: Figure 1). Note that this is a strong test since the baseline data are wholly independent of the model training data. Also, see Smart et al. (2019) for further testing of MultiMOVE. We consider that these results indicate a useful level of model performance in predictive mode.

3.2 | Modelling change as a function of agri-environment scheme intervention and climate

3.2.1 | Baseline and projected climate

The observed baseline (1981–2016 averages) and the high emissions (RCP8.5) predictions are notably different, although there is an overlap in value ranges (Supplementary Material 5: Figure 4). Annual rainfall values are all within the range of the MultiMOVE training data (Supplementary Material 5: Figure 4A). However, for temperature (especially minimum Jan temperature, Supplementary Material 5: Figure 4B) a spike in projected values in 2026 moves outside the range of the GB-wide training data resulting in a lack of robustness in model performance for these locations; thus, these results are omitted from the figures here.

3.2.2 | Projected change in soil conditions

Across the three scenarios, the modelled direction of change in soil variables was similar with small differences between habitat types (Supplementary Material 4: Figure 1). Overall, improved and neutral grasslands tended to increase in %C and decrease in %N but changes were small over the time period. The predicted change was more marked in acid grasslands where both %C and %N were expected to decrease. Modelled changes in pH varied the most, increasing in the LI and RS scenarios and decreasing under no fertiliser inputs (Supplementary Material 4: Figure 1).

3.3 | Modelled habitat suitability and vegetation change over 13 years

3.3.1 | Plant species and dark diversity changes grouped by link to function and service

The suitability of conditions for injurious weeds remained stable (acid grasslands) or declined (improved and neutral grasslands) in all scenarios seeing a more gradual decline up to 2029 under the RS scenario. Nitrogen-fixers were also largely stable but habitat suitability was predicted to increase under LI and RS in improved and neutral grassland (Figure 2). Stability and decline in habitat suitability in the later part of the interval were projected in acid grassland for nitrogen-fixers (Figure 2).

Modelled diversity of both nectar plants and forage grasses was predicted to increase in the majority of grassland and management scenario combinations but with a decline in the suitability of conditions for these groups of species in acid grassland under RS up to 2029. Within the acid grassland broad-habitat increases in forage grasses were only predicted given management for taller vegetation (>100mm) or under-predicted climate change (Figure 2).

Including predicted climate change made little overall difference to forecast changes in diversity between 2016 and 2021. However, between 2021 and 2029 predicted climate values were estimated to drive declines in the suitability of conditions for a number of functional groups including nectar plants and nitrogen-fixers in improved grasslands under LI and NI (Figure 2).

Modelled changes in responses of functionally important species were consistent with the longer-term aim of reducing management intensity. For example, suitability increased for less-productive forage grasses such as *Anthoxanthum odoratum* (Supplementary Material 5: Figure 5), and decreased for injurious weeds such as *Rumex obtusifolius* (Supplementary Material 5: Figure 6). Consistent with a reduction in management intensity a net increase in habitat suitability was projected for a range of common nectar plants (associated with lower agricultural intensity). Examples include *Cirsium palustre* and *Lotus corniculatus*, both showing small but consistent increases in habitat suitability for all scenarios (Supplementary Material 5: Figures 7 and 8). Within the nitrogen-fixing species group a consistent pattern was only seen in acid grasslands (Figure 2); where across the extensification scenarios, nitrogen-fixer diversity was typically maintained or declined somewhat by 2029 (Supplementary Material 5: Figure 3).

3.3.2 | Vegetation community change

Modelled outcomes of all three extensifying scenarios were similar with or without climate change since predicted climate changes were small over the interval (Figure 3). The same National Vegetation

Scenarios	Scenario setting	Improved grassland species groups: Nitrogen fixing	Improved: Nectar plants	Improved: Forage grasses	Improved: Injurious weeds	Neutral grassland species groups: Nitrogen fixing	Neutral: Nectar plants	Neutral: Forage grasses	Neutral: Injurious weeds	Acid grassland species groups: Nitrogen fixing	Acid: Nectar plants	Acid: Forage grasses	Acid: Injurious weeds
Low inputs	Baseline climate & vegetation < 7 cm	+	+	+	-	+	+	+	0	0	+	0	0
	Baseline climate & vegetation > 7 cm	+	+	+	-	0	+	+	0	0	+(-)	0	0
	Projected climate & vegetation < 7 cm	+	+	+	-	0	+	+	0	+	+(~)	+	0
	Projected climate & vegetation > 7 cm	0(-)	+(-)	+	0	0	+	+	0	0	+(-)	+(~)	0
No Inputs	Baseline climate & baseline vegetation	0	+	+	-	0	+	+	0	0	+(~)	0	0
	Projected climate & baseline vegetation	0(-)	+(-)	+	-	0	+(-)	+	0	0	+(-)	0	0
Reduced stocking	Baseline climate & vegetation < 7 cm	+	+	+	0(-)	+	+	+	0(-)	0	+(-)	0(-)	0
	Baseline climate & vegetation > 7 cm	0(-)	+	+	0(-)	+(-)	+	+	0(-)	0(-)	+(-)	+(-)	0
	Projected climate & vegetation < 7 cm	+	+	+	0(-)	0	+	+	0(-)	0(-)	+(-)	0(-)	0
	Projected climate & vegetation > 7 cm	0(-)	+(-)	+	0(-)	0(-)	+(-)	+	0(-)	0(-)	+(-)	0(-)	0

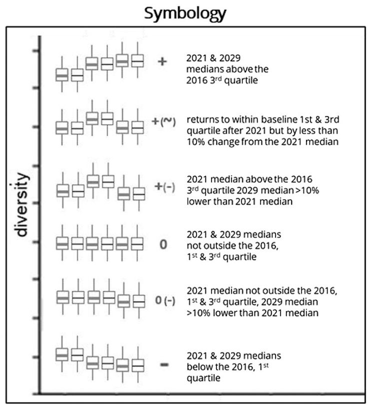

FIGURE 2 Modelled diversity across years (2016, 2021, 2029) of plant species supporting ecological functions and services (Smart et al., 2017). See inset for interpretation of symbols conveying a change in diversity. Supplementary Material 5: Figure 3A,B for boxplot trends. Scenarios represent three groups of grassland management options representative of agri-environmental schemes (see Supplementary Material 4: Table 1B). Scenarios were created using baseline (2016) and predicted climate data (UKCP18) combined with management-driven predictions of soil change as inputs to the plant species ecological niche models available in MultiMOVE. The 7 cm vegetation height is stipulated as a target sward height in the relevant AES scheme option: Welsh Government (2016).

Classification (NVC; Rodwell, 1998) units featured among the best fits with and without climate change. Over the 13-year interval, conditions became more suitable for semi-improved and unimproved grassland communities at the expense of improved grassland communities (Figure 3). Introducing climate change, therefore, had minor effects on change in the distribution of best-fitting community units. The effect of the RS scenario in acid grassland was less consistent with expectations. Here unimproved communities decreased in favourability with small net gains to semi-improved grassland, fen and assemblages typical of more disturbed conditions.

By 2029 (Figure 3), the greatest impact of the extensifying scenarios was predicted to be in the more productive neutral and improved grasslands with more occurrences of later successional and less productive NVC community types including the Bracken-dominated U20 (*Pteridium aquilinum-Galium saxatile* calcifugous grassland) and W25 (*P. aquilinum-Rubus fruticosus* agg. underscrub) but also greater fits to a range of semi-improved grassland types. The greater variation in vegetation types that was expected to arise following AES intervention suggests a degree of dependence on starting conditions. Overall, then, modelling suggests that a desirable shift in conditions favouring plant community types more typical of lower fertility could be achieved in 13 years as shown in Figure 3. Up to 5 years, the typical AES agreement length, much less change is predicted, see, Supplementary Material 5: Figure 2.

By 2029, modelled assemblages within improved grassland, showed greatest matches with community units still dominated by productive forage grasses chiefly MG6 *Lolium perenne-Cynosurus cristatus* grassland. Moreover, in many places, the improved and highly productive MG7 grassland, strongly dominated by *L. perenne*, still featured in the best fit to modelled species compositions. This suggests that the most productive grasslands can still prove resistant to extensification even after 13 years of management.

In response to the predicted effects of 13 years of AES intervention modelled assemblages were also a frequently higher match with wetter, yet still productive grasslands, dominated by the common and abundant rush *Juncus effusus* and the common grass *Agrostis stolonifera*; NVC communities MG10 *Holcus lanatus-J. effusus* rush pasture and MG11 *Festuca rubra-A. stolonifera-Potentilla anserina* grassland. After 13 years, modelled species compositions within neutral grasslands were also often the best match to the widespread, U4 *Festuca ovina-Agrostic capillaris-G. saxatile* grassland, typically less fertile and with lower pH but where species persist that are indicative of agricultural improvements such as *Holcus lanatus* and *Trifolium repens*. While the modelled impact of extensifying interventions appeared to drive a shift towards assemblages typical of less productive and lower pH conditions this did not result in predicted species compositions that matched the characteristically more species-rich lowland unimproved neutral grasslands; MG4 *Alopecurus pratensis-Sanguisorba officinalis*, MG5 *C. cristatus-Centaurea nigra* and MG8 *C. cristatus-Caltha palustris* communities. This is despite the fact that species typical of these assemblages will have been present in most species pools and therefore potential contributors to the modelled dark diversity of each patch. In none of the random samples of grassland plots did these unimproved hay meadow assemblages feature in the top five best fits. This is perhaps not surprising given the rarity of these traditionally managed hay meadows in Wales (Alison, 2020; Stevens, 2010). The implication from our modelling is that in most places, changes in soil conditions and possibly canopy height, are not expected to be sufficient to favour the rarest neutral grassland communities. Even where such conditions do arise, assisted

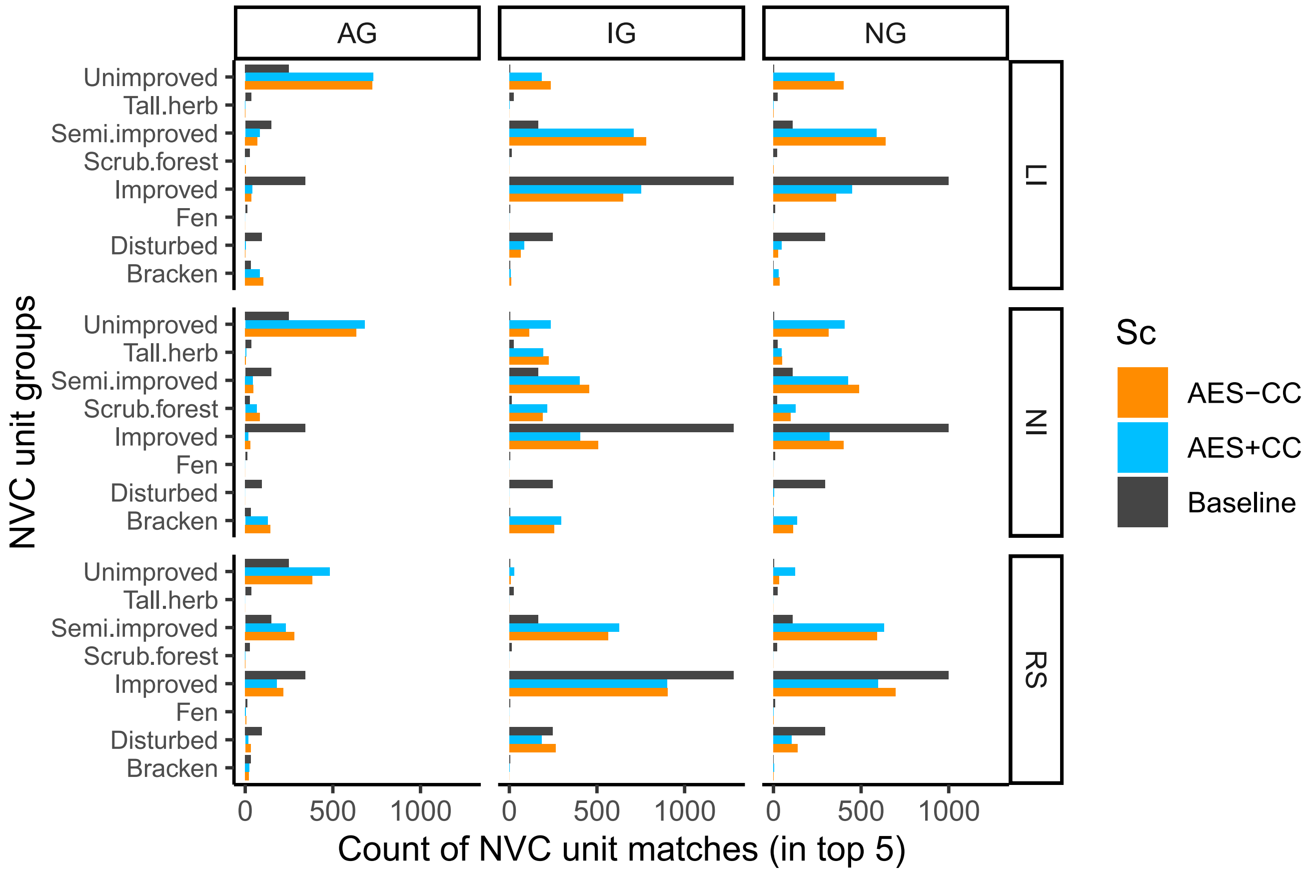

FIGURE 3 Plant community profiles of modelled baseline (2016) versus scenario-driven species composition (2029). Each graph shows the counts of matches by community type where each type featured in the top five matching coefficients when the modelled habitat suitability values for each quadrat were compared to the species compositional profiles of the UK National Vegetation Classification (NVC). Modelled baseline (dark grey); AES-only with no climate change (orange), AES + predicted climate change to 2029 (blue). Broad-habitat types: IG = Improved grassland (348 plots); NG = Neutral grassland (292 plots); AG = Acid Grassland (188 plots). For Low Inputs (LI) and Reduced stocking (RS), vegetation height was set to 10 cm (Table 1). Under No Inputs (NI) vegetation height was not changed from baseline. Summarised vegetation types were derived by grouping (Supplementary Material 5: Table 2) NVC unit matches for the baseline and modelled GMEP plots. Matches are from MAVIS processing of the habitat suitability outputs from ecological niche modelling. Predictions to 2021 are omitted because few changes were predicted. Note that all plots were located in habitat areas mapped at baseline as one of the three grassland types however the detailed plant community composition may vary at each plot location within these areas. Unimproved, semi-improved and improved refer to groups of grassland NVC units that vary in productivity.

dispersal and establishment may be required. Modelled changes applied to the lower soil pH acid grassland starting points may have been expected to result in increasing fits to heathland assemblages. However, we only applied a minor change in canopy height consistent with the interventions modelled. A taller canopy height filter will have increased the possibility of admitting taller heathland ericoids into the estimated dark diversity for each location conditional on the soil regime (cf. Medina-Roldán et al., 2012).

4 | DISCUSSION

The benefits of our approach are simplicity plus high realism and generality. This is because we modelled at fine resolution but across a representative national sample of locations. Using an AES survey as a baseline for modelling also derives more value for money from these costly field campaigns while also addressing calls for better use of modelling to understand the ecological impacts of interventions (Horrocks et al., 2014; Kleijn & Sutherland, 2003; Lavorel et al., 2011; Staley et al., 2018).

4.1 | Modelling the management scenarios

We conclude that given sufficient time (>10 years), the three extensifying management scenarios appear likely to drive desirable changes in soil carbon and nitrogen, which in turn increase the likelihood of achieving maintenance and restoration outcomes for plant communities and species groups. Hence, 13 years of low to no inputs, creates conditions more suitable for plant community types associated with lower fertility. This is consistent with Critchley et al. (2004) who also showed that plant community restoration could occur in a range of grassland types in Britain in parallel with reductions in soil fertility within 4–8 years.

In the modelled scenarios, the low-fertility acid grassland showed the greatest increase in the range of vegetation community types but not necessarily to markedly lower-fertility assemblages (Figure 3). In contrast, the higher fertility improved and neutral grasslands showed greater shifts from their baseline with significant gains to unimproved and semi-improved grassland types. Less fertile starting conditions (acid grassland) not only have less productivity to lose but also appear to show the greatest diversification in community type in response to 13 years of extensifying management. These patterns are to some extent consistent with the dependence of responses on varied starting conditions (Critchley et al., 1996).

Our results predict the changing habitat suitability of species that arise when we filter the species pool by adjusting grazing regime via impact on vegetation height, nutrient inputs via impact on soil conditions and climate. We emphasise that we did not model dispersal, plant establishment and population dynamic processes that result in the formation of dominance heirarchies and realised alpha diversity (Gavish et al., 2017). For example, reduced nutrient inputs and grazing reduces the vigour of perennial grass cover providing gaps that can be rapidly exploited by injurious weeds even though the suitability of abiotic conditions is expected to decline over the longer term (Maskell, Henrys, et al., 2020). Therefore, change in modelled suitability of conditions may not correlate positively with short-term changes in abundance. Moreover, immigration events underpinning species compositional turnover may well lag behind abiotic changes that result from reduced nutrient inputs (Boulangeat et al., 2012) or not occur at all unless further intervention assists dispersal and establishment (Wagner et al., 2014). This is consistent with our treating vegetation patches as unsaturated (Mateo et al., 2017) meaning that our outputs should be interpreted as an estimation of the potential pool of suitable species that will themselves be filtered as a result of local and regional processes (Pärtel et al., 2011).

We adopted a simple data-driven approach to modelling soil change over a relatively short time interval, deliberately chosen to reflect the duration of scheme agreements (5–13 years). The trends we projected have indeed been observed under extensification (Marriott et al., 2010; Medina-Roldán et al., 2012) including increasing soil C, decreasing fertility and small biodiversity gains (Medina-Roldán et al., 2012). This is most consistent in our modelling of neutral grassland (Supplementary Material 4: Figures 1 and 3).

We believe that there was sufficient consistency in the available soil observations to produce robust models but note that long-term experimental data that can be used to represent extensification AES options reliably appears to be rare (see Sections 2.6 and 2.9 above; and Supplementary Material 4). Despite a number of long-term experiments existing across the United Kingdom, we found a surprising lack of long-term datasets that could represent changes in soil variables driven by fundamental processes of succession, disturbance and changes in macro-nutrient availability in response to management. We are not alone in noticing this (Chazal & Rounsevell, 2009).

We show that all three AES scenarios were predicted to diversify the range of plant communities relative to baseline. However, much more limited change was estimated to occur over 5 years; the typical duration of Glastir scheme agreements (Supplementary Material 5: Figure 2). Our results suggest that AES stakeholders interested in evidence from monitoring programs should expect little major change after 5 years when newly applying AES prescriptions, but continuing management is capable of creating conditions suitable for target communities and plant species. Stevens (2010) also described the lower impact of such interventions expected in the shorter term on Welsh grasslands. Modest impacts over similarly short timescales have been seen elsewhere in temperate grasslands (Marriott et al., 2010; Medina-Roldán et al., 2012; Norton et al., 2014).

4.2 | Climate change and plant diversity

Given the short time interval across which we modelled, we applied a worst-case-scenario future climate projection to explore the potential strength of the modelled responses on an annual basis (e.g. Morecroft et al., 2016). Climate was not predicted to change greatly over the interval, and this undoubtedly contributed to the relatively greater modelled impact attributable to AES intervention.

Inspecting the time series of annual projections showed considerable variation with a peak in temperature in 2026 that moved outside of the training space of our ENM ensemble (Lowe et al., 2018; Met Office Hadley Centre, 2018), Supplementary Material 5: Figure 4. This exemplifies the challenge of any model to reliably project species niche dynamics into novel climate space (Fitzpatrick & Hargrove, 2009; Veloz et al., 2012; Williams & Jackson, 2007). Even though the 2021 and 2029 projected climate variables were within the model's training space, novel configurations of climate variables become much more likely in future (Alexander et al., 2016; Mouquet et al., 2015). This challenges the modelling community to achieve useful prediction by modelling genotypic and phenotypic adaptive capacity at the species level. Achieving this would free ENM from the constraints imposed by the range of their historical training data (Benito Garzón et al., 2019). This is an active research frontier and approaches vary in data demand (Benito Garzón et al., 2019; Catullo et al., 2015; Mokany et al., 2019). For our purposes, species' adaptive capacity is arguably less relevant to our results as we consider an interval ending relatively soon in 2029 and defined to explore AES performance under realistic agreement lengths (Rose, 2011).

We estimate that the effect of the extensifying interventions will substantially outweigh modelled climate change effects in the time period modelled (Figures 2 and 3; Supplementary Material 5: Figures 2 and 3). The strong effect of management relative to other drivers clearly depends upon the severity of the driver (Guiden et al., 2021) and future directional change in climate accompanied by acute effects of extreme events is increasingly likely (Dodd et al., 2021). Because we were interested in modelled impacts over a relatively short near-term interval and interested in the effects of the weather in any one year, we applied annual predicted climate variables. In so doing we generate an instantaneous predicted habitat suitability for each species in the modelled pool filtered by the predicted value of each climate variable. The same applies to the impact of predicted soil variables each year. The difficulty is in interpreting what this means in terms of above- and below-ground ecological change. There are likely to be legacy effects of previous years' weather cumulatively altering the relative abundance of plants already present and changing opportunities for colonisation and local extinction. We do not model the complex interplay of these directional, cyclic and random dynamics but, instead, take a simpler, but we believe, informative approach more akin to a prospective risk assessment of future impact. Had the predicted climate in each year of our study been consistently and markedly warmer or colder than baseline we would predict a strong filtering effect of climate on habitat suitability that could then be usefully compared with future observations (cf. Morecroft et al., 2016; Rose et al., 2016).

Based on our model investigation we estimate that up to the end of this decade predicted climate change will be a minor driver of change in the diversity of a number of functionally important species groups. While climate impacts are more noticeable up to 13 years, the impact of AES interventions on habitat suitability for plants is likely to be a stronger driver of potential species compositional turnover.

4.3 | Management effects and time-scales

Over the modelled time period, changes in soil variables were predicted to be modest and consistent with observed responses in the time series used to build the soil models (e.g. Defra, 2015; Pywell et al., 2007). These changes drove clear shifts towards conditions more suitable for unimproved grassland communities by 2029 with much less change predicted by 2021 (Supplementary Material 5: Figure 2). Therefore, longer durations should bring about more desirable change (Horrocks et al., 2014). This is consistent with other research suggesting that either management must carry on for longer to see a change or that interventions should be more impactful per unit of time under agreement (Hayes & Lowther, 2014; Kirkham et al., 2011; Marriott et al., 2010; McSherry & Ritchie, 2013; Medina-Roldán et al., 2012; Pywell et al., 1994). We estimate that just 5 years of AES management intervention is likely to result in limited benefit to the plant species groups explored here.

5 | CONCLUSIONS

The AES prescription scenarios represented in our results are all a form of broad-shallow extensification of management. These lighter-touch AES prescriptions are more acceptable to grassland agricultural managers because they require fewer changes in practice (Arnott et al., 2018). Our modelling suggests that these interventions can produce positive effects if given enough time (at least 10 years).

AUTHOR CONTRIBUTIONS

Bede West and Simon M. Smart conceived the initial ideas and aims, Bede West then constructed the model workflow and soil change review with the neural networks contributed by Simon M. Smart and the climate data by Emma L. Robinson, all other data is sourced as referenced in or within the acknowledgements. Bede West led the writing of the manuscript with contributions from all other authors to the drafts and final approval for submission.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

Summarised modelling data can be found within the Supplementary Material and baseline datasets are within the following references: Smart et al. (2020), Maskell, Astbury, et al. (2020) and Robinson et al. (2019).

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SUPPORTING INFORMATION

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

Supplementary Material 1. Description of grassland Broad Habitat Types
Supplementary Material 2. Downscaled climatic variables.
Supplementary Material 3. Ellenberg indices neural net calibration.
Supplementary Material 4. Modelling change in soil variables given management intervention
Supplementary Material 5. Workflow output graphical plots.

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