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The National Plant Monitoring Scheme: A Technical Review

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EQA

Sections 2.1, 2.5, 3.1 & 3.3 have been externally peer reviewed whilst the remaining sections were internally reviewed to comply with the JNCC Evidence Quality Assurance Policy https://jncc.gov.uk/about-jncc/corporate-information/evidence-quality-assurance/.

Summary

The National Plant Monitoring Scheme, coordinated by the Botanical Society of Britain and Ireland, the Centre for Ecology & Hydrology, JNCC and Plantlife, was launched in 2015 to provide an indication of the status and trends of plants and semi-natural habitats across the UK. The scheme is based on volunteer recording according to a set protocol at pre-determined monads selected through a weighted-random sampling scheme. The approach and specific methodology was agreed following several years of development by experts, and is summarised in Pescott *et al*. (2019) and on the NPMS website (http://www.npms.org.uk). Following two years of NPMS data collection, the NPMS partnership carried out this review of the scheme, documenting how its establishment is progressing, and exploring how the accumulating data could be analysed, and the scheme put to best use.

The review is divided into three sections:

First, a review of the data being obtained is presented. This includes information on the level of sampling uptake, geographical coverage, habitat and species coverage, and the frequency of recording of scheme indicator species. This section finishes with a consideration of the biases inherent to this data collection, and sets out future options for quality assurance.

Second, the review considers the analysis of scheme results, including trends in species and habitats, and some initial development work on a habitat condition indicator. Whilst an initial power analysis was carried out during scheme method development (Pescott *et al*. 2016), it was considered valuable to revisit this in the context of actual data being collected by the scheme, and ongoing improvements to analytical techniques.

Finally, the review considers how the scheme could be used beyond these basic outputs on species and habitat statuses and trends. This section considers the extent to which the NPMS could meet a range of contemporary policy and conservation needs, either alone or when used in combination with other data sources. Needs such as biodiversity reporting and assessing the success of agri-environment schemes are considered. This final section also looks to the future, considering how both greater practical and analytical integration with other biodiversity recording could increase data usefulness, and how data could be used in rapidly developing technologies such as Earth Observation analysis.

A concise summary of the main findings can be found in the summary boxes at the start of each chapter. Further detail can be found in the main text and in the online appendices and annexes to this report.

Contents

1 NPMS Data

1.1 Geographic coverage

Following a number of years of planning and field trials of survey methodology, the new National Plant Monitoring Scheme (NPMS) has now completed its first two field seasons. The geographic coverage of sample plots across the UK and Channel Islands is good, and the project is striving to recruit more volunteer surveyors to achieve more extensive coverage and survey effort in future years. One-thousand, seven-hundred, and twenty-three (1723) plots were surveyed in 2015 and 1,874 plots in 2016, with a total of 2,529 unique plot locations.

Five-hundred and eighty-eight (588) unique 1 x 1 km squares (monads hereafter) were surveyed in the period 2015-2016, with 403 monads surveyed in 2015 and 446 in 2016. Within the monads surveyed, 2,529 unique plots (i.e. unique spatial locations) were surveyed. These were visited a total of 3,597 times, with 1,723 plots surveyed in 2015 and 1,868 plots in 2016. From 2015 to 2016, the number of monads surveyed increased by over 10% and the number of individual monitoring visits increased by around 9%. There was a marked increase in Northern Ireland and Scotland, while in England and Wales there was little difference between years. Table 1 represents a breakdown of monads and plots surveyed by country.

Table 1. Number of monads and plots surveyed by year and country.
Note: when a monad straddled a country boundary (n = 9), the information was recorded under both countries for the information in this table.

Country	Number of monads surveyed		Unique monads	Number of plots surveyed		Unique plot locations
	2015	2016		2015	2016	
Channel Isles	1	1	1	5	5	5
England	297	302	409	1,279	1,258	1,757
Northern Ireland	7	23	26	26	88	97
Scotland	50	75	91	210	337	403
Wales	48	45	61	203	186	267
Total	403	446	588	1,723	1,874	2,529

The survey monads are relatively evenly distributed across the UK (Figure 1). However, in common with many other surveillance schemes, remote areas and uplands are under-represented (see also Pescott *et al*. 2019). As the scheme develops over the next few years, it is intended to increase the coverage across the country to make the dataset more robust in the long term. Particular attention will be given to under-represented areas through targeted stakeholder interactions.

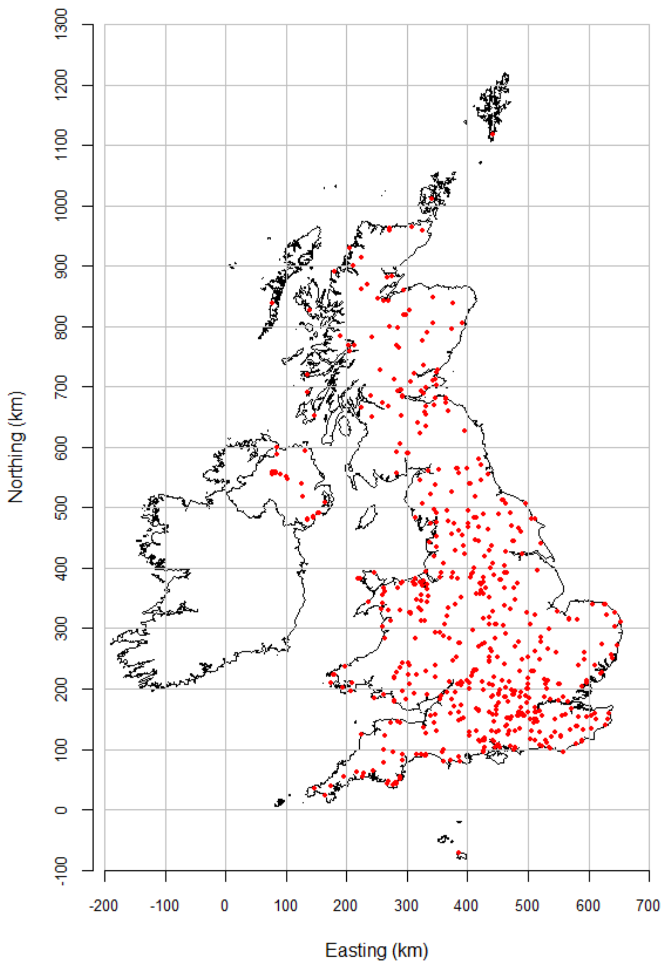

Figure 1. Distribution of NPMS monads monitored in the 2015 and 2016 field seasons.

1.2 Habitat coverage

> The NPMS has developed a habitat classification with 11 broad habitat categories and 28 fine habitat categories. The NPMS habitats have been cross-referenced to Annex I, EUNIS, NVC and UK priority habitats. The NPMS survey squares are a weighted random selection, with the weights promoting the selection of rarer, semi-natural UK habitat types. As part of the sampling protocol volunteers confirm the specific habitat of their plots. The spread of habitat types across the sampled NPMS plots across the UK is good. The most frequently surveyed habitat types are broadleaved woodland and lowland grassland, while certain montane habitat types and raised bog are the least surveyed. None of the survey plots currently include machair. The project aims to direct greater survey effort in future years to better capture under-represented habitats.

The NPMS covers a wide range of semi-natural habitats comprising 11 broad habitat categories split into a total of 28 fine habitat categories. The habitat descriptions can be found within the NPMS field survey guidance notes available on the scheme website (http://www.npms.org.uk/content/resources). The scheme habitat classification was developed based on EUNIS Level 2 and the British National Vegetation Classification (NVC), and was peer-reviewed by a range of experts (Pescott *et al*. 2014a). The equivalences between the NPMS habitat classification and both EUNIS, Annex 1 habitats and the NVC can all be found in Pescott *et al*. (2017) as well as on the NPMS website (http://www.npms.org.uk/content/conservation-and-research). A summary of the coverage of NPMS ‘broad’ and ‘fine’ scale habitats is set out below (Table 2 and Table 3), broken down by country.

The data associated with this review task are presented in online Appendix 1. This spreadsheet presents the habitat samples that have been recorded in the first two years of the scheme, being 2015 and 2016. A sample is a unique visit to an established NPMS plot. Details of how plots are selected and surveyed can be found in Walker *et al*. (2015) and the NPMS guidance notes linked above, and are not repeated here. The spreadsheet also indicates the species richness associated with a sample, as well as the recorded habitat, the vice-county, country, monad and 10 x 10 km square (hectad hereafter). Metadata are also provided in the spreadsheet. EUNIS, Annex 1 and Priority Habitat equivalence information is also included for convenience; a ‘naïve’ equivalence column is also provided, this presents the matched habitats for a particular classification without any supporting text to allow for easier computational manipulation.

A comparison between the habitat types recorded by NPMS surveyors in the field and those indicated by land cover mapping data (specifically the Land Cover Map 2015), has been conducted and presented elsewhere (Pescott *et al*. 2019). The general conclusions from the analysis of Pescott *et al*. (2019) were that broadleaved woodland and lowland grassland were widely surveyed, as expected from mapping data, whereas other habitat types, e.g. acid grassland/heathland and montane grassland, are likely to be under-represented in relation to the indications of the land cover mapping data; coastal habitats, on the other hand, may be over-represented. There was also evidence for the good take-up of habitats that are not represented by the land cover product used, namely arable field margins and small acidic or basic wetland features (i.e. fens, mires, and springs).

1.2.1 Broad habitat category coverage

All 11 broad NPMS habitat categories were surveyed in both 2015 and 2016. The broad habitat categories are (ranked from highest to lowest number of plots): broadleaved woodland, lowland grassland, arable field margins, coast, heathland, freshwater, bog and wet heath, marsh and fen, upland grassland, rock outcrops cliffs and screes, and native pinewood and juniper scrub. The Channel Islands had the least number of broad habitat categories with only four surveyed: arable field margins, broadleaved woodland, freshwater and lowland grassland; this is not surprising giving that the area covered is small, and that there was only one monad being surveyed in the period covered by this report. Northern Ireland had eight broad habitat categories surveyed, missing arable field margins, native pinewood and juniper scrub, and upland grassland. England and Wales lacked only the native pinewood and juniper scrub category whilst all broad habitat categories were surveyed in Scotland.

Table 2. Number of plots (i.e. unique spatial locations) per broad habitat category, per year, per country. Where plots were recorded to the NPMS fine habitat category, these plot counts were aggregated to broad habitat category.

NPMS broad habitat category	2015						2016					
	Channel Islands	England	Northern Ireland	Scotland	Wales	Total	Channel Islands	England	Northern Ireland	Scotland	Wales	Total
Arable field margins	1	120	0	7	2	130	1	114	0	10	0	125
Bog and wet heath	0	43	7	33	9	92	0	42	28	46	8	133
Broadleaved woodland	1	483	6	38	54	582	1	474	19	50	49	593
Coast	0	66	0	15	20	101	0	70	7	25	30	132
Freshwater	0	79	0	12	12	103	1	69	9	23	12	114
Heathland	0	77	2	24	12	115	0	71	2	29	5	107
Lowland grassland	2	357	6	44	56	465	2	371	19	91	54	537
Marsh and fen	0	38	4	16	13	71	0	34	4	24	9	71
Native pinewood and juniper scrub	0	0	0	12	0	12	0	0	0	27	0	27
Rock outcrops, cliffs and screes	0	13	1	6	8	28	0	14	0	7	8	29
Upland grassland	0	14	0	5	19	38	0	12	0	9	15	36
Not in scheme	1	12	0	2	1	17	0	11	1	2	1	15
Total number of plots	5	1,302	26	214	207	1,754	5	1,282	89	343	191	1,910

1.2.2 Fine habitat category coverage

Out of the 28 fine habitat categories, 27 were represented in both 2015 and 2016. The fine habitat categories are ranked from highest to lowest number of plots surveyed: hedgerows of native species, dry deciduous woodland, neutral pastures and meadows, arable field margins, dry heathland, dry calcareous grassland, neutral damp grassland, wet heath, dry acid grassland, rivers and streams, wet woodland, acid fens, flushes, mires and springs, nutrient-rich lakes and ponds, coastal saltmarsh, coastal vegetated shingle, montane acid grassland, coastal sand dunes, blanket bog, maritime cliff tops and slopes, base-rich fens, flushes, mires and springs, conifer pinewood and juniper scrub, inland rocks and scree, dry montane heathland, montane calcareous grassland, and raised bog. There were no records for machair.

There was variable coverage of fine habitat categories within countries. England had 26 of the fine habitat categories in both sampling years, while Scotland had 24 and 25, and Wales 25 and 23 in 2015 and 2016 respectively. In Northern Ireland, 8 and 15 of the fine habitat categories were surveyed. While some habitat categories are consistently well represented, others are confined to one or two countries only. For instance, the greatest number of plots with coastal vegetated shingle and dry calcareous grassland are found in England, while all conifer pinewood and juniper scrub plots are in Scotland, and montane acid grassland plots have been mainly recorded in Wales.

Table 3. Number of plots per fine habitat category, per year, per country.

NPMS fine habitat category	2015						2016					
	Channel Islands	**England**	**Northern Ireland**	**Scotland**	**Wales**	**Total**	**Channel Islands**	**England**	**Northern Ireland**	**Scotland**	**Wales**	**Total**
Acid fens, flushes, mires and springs	0	16	4	8	9	37	0	17	4	12	8	41
Arable field margins	1	120	0	7	2	130	1	114	0	10	0	125
Base-rich fens, flushes, mires and springs	0	13	0	7	2	22	0	9	0	11	1	21
Blanket bog	0	10	3	7	1	21	0	14	0	9	4	27
Coastal saltmarsh	0	19	0	1	3	23	0	19	2	5	8	34
Coastal sand dunes	0	4	0	8	6	18	0	7	4	10	10	31
Coastal vegetated shingle	0	23	0	3	1	27	0	24	1	3	3	31
Conifer pinewood and juniper scrub	0	0	0	12	0	12	0	0	0	27	0	27
Dry acid grassland	2	16	0	8	18	44	1	19	2	12	16	50
Dry calcareous grassland	0	68	0	0	4	72	0	87	0	8	9	104
Dry deciduous woodland	1	197	1	17	13	229	1	203	1	24	8	237
Dry heathland	0	68	2	16	4	90	0	65	2	24	2	93
Dry montane heathland	0	3	0	5	3	11	0	1	0	0	3	4
Hedgerows of native species	0	218	5	8	24	255	0	206	15	12	26	259
Inland rocks and scree	0	8	0	2	5	15	0	9	0	5	6	20
Maritime cliff tops and slopes	0	15	0	1	7	23	0	12	0	5	5	22
Machair	0	0	0	0	0	0	0	0	0	0	0	0
Montane acid grassland	0	6	0	5	17	28	0	2	0	4	15	21
Montane calcareous grassland	0	3	0	0	2	5	0	7	0	1	0	8
Montane rocks and scree	0	4	1	3	3	11	0	4	0	0	2	6
Neutral damp grassland	0	52	0	20	4	76	0	37	4	30	6	77
Neutral pastures and meadows	0	157	1	8	22	188	1	156	3	16	18	194
Nutrient-poor lakes and ponds	0	12	0	5	1	18	0	9	0	7	1	17
Nutrient-rich lakes and ponds	0	27	0	3	2	32	1	29	3	5	2	40
Raised bog	0	1	0	0	0	1	0	1	1	1	0	3
Rivers and streams	0	30	0	3	8	41	0	23	5	8	9	45
Wet heath	0	20	4	21	7	52	0	11	5	32	4	52
Wet woodland	0	37	0	5	6	48	0	31	2	6	5	44
Grand Total	4	1,147	21	183	174	1,529	5	1,116	54	287	171	1,633

1.3 Species coverage

The NPMS has developed a set of species indicators for all habitats covered by the scheme. Volunteer recorders can choose to survey plots at 'Wildflower', 'Indicator' or 'Inventory' level. At Wildflower level, volunteers record a subset of the Indicator list. At Indicator level, volunteers record all species on the Indicator list. At Inventory level volunteers record all species on the Indicator list and any other vascular plants present (i.e. they record all vascular plants). This brings variability into the dataset, but it allows for wider volunteer participation, meaning that a larger number of squares are likely to be surveyed. Twenty-seven percent of volunteers recorded plots at the Wildflower level, 36% recorded at the Indicator level and 37% recorded at the Inventory level. A total of 1,280 taxa were recorded in 2015 and 2016. Habitat categories were evaluated in terms of likelihood to detect a trend with at least 30 samples of a single indicator species. At the UK level, 8 out of 11 broad habitat categories had at least one indicator species recorded in at least 30 plots in both survey years. At a country level, England, Wales and Scotland had indicators recorded in at least 30 plots for at least two broad habitat categories, whilst the Channel Islands and Northern Ireland had none.

In the NPMS, surveyors can choose to record at three different levels depending on their experience and skills in identifying vascular plants: Wildflower, Indicator and Inventory. Each fine habitat category has a list of indicator species and the survey level of the volunteer affects which species the volunteer records. Indicator species are associated with the condition of each fine habitat category with positive indicator species indicating positive habitat condition and vice versa for negative species. At the Wildflower level, surveyors record a subset of the indicator species for that habitat. At Indicator level, volunteers record all species on the indicator list. At Inventory level, volunteers record all species on the indicator list as well as any additional vascular plants present. The records are validated and verified through the activities of expert botanists (often BSBI vice-county recorders) on iRecord (www.brc.ac.uk/irecord), combined with NBN Record Cleaner validation checks. Summaries of species coverage are set out below including the effect of volunteer recording level and coverage of indicator species.

The data associated with this review task are presented in full in online Appendix 2. This spreadsheet contains all of the taxon records made by NPMS surveyors within the first two years of the scheme. The spreadsheet also presents information about surveyor level, habitat, and verification status to help contextualise each record.

1.3.1 Interaction with recording level

As noted above, NPMS volunteer recorders can choose to survey their squares at one of three levels ('Wildflower', 'Indicator' or 'Inventory'), depending on the skill level of the surveyor. At Wildflower and Indicator levels the surveyor is given a list of species to record, while at Inventory level the surveyor aims for a complete record of the plot. On average, one third of the surveys were carried out at each of the three recording levels (Table 4). The split in England, Scotland and Wales is very similar, while in Northern Ireland all the recording was carried out at Indicator and Inventory levels. Across all habitats there was no obvious spatial bias relating to the level of recorder participation (Figure 2).

Table 4. Percentage of surveys carried out at each level of the scheme.

Scheme Level	Channel Islands	England	Northern Ireland	Scotland	Wales	Overall
Wildflower level	0	28	0	29	30	27
Indicator level	0	36	61	36	32	36
Inventory level	100	37	39	34	38	37

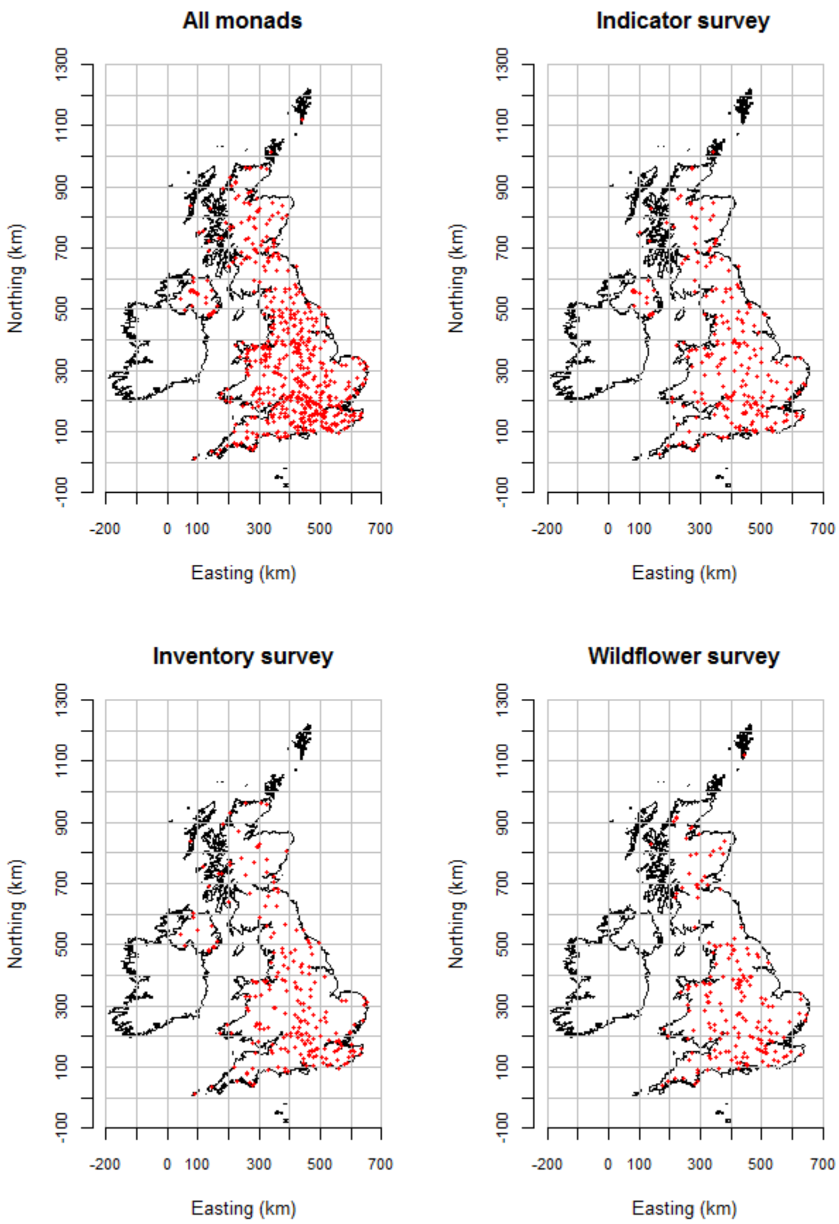

Figure 2. Maps of all UK monads, and of those containing at least one plot of the named surveyor type (Wildflower, Indicator, Inventory).

1.3.2 Number of taxa (species or species groups) recorded in each habitat type

A total of 1,280 taxa were recorded in 2015 and 2016, many of them in several habitat types (Table 5). While most of these refer to species, the dataset includes a significant proportion of records that have been identified to a higher taxon level (mainly genus). There are several possible reasons for this, including the fact that specimens lacking diagnostic features can sometimes be encountered, some species may also be generally difficult to identify, regardless of stage; surveyor experience is also likely to play a part in this.

Table 5. Number of taxa (including higher taxa) recorded in each habitat type.

NPMS broad habitat	NPMS fine habitat	Number of taxa		
		2015	2016	2015/16
Arable field margins	Total	239	244	313
	Arable field margins	239	244	313
Bog and wet heath	Total	146	161	201
	Blanket bog	56	67	90
	Raised bog	19	16	31
	Wet heath	113	122	158
Broadleaved woodland	Total	574	599	734
	Dry deciduous woodland	328	342	429
	Hedgerows of native species	403	397	506
	Wet woodland	186	179	243
Coast	Total	259	362	420
	Coastal saltmarsh	43	66	83
	Coastal sand dunes	116	174	195
	Coastal vegetated shingle	148	115	181
	Machair	0	0	0
	Maritime cliff tops and slopes	61	126	150
Freshwater	Total	391	345	470
	Nutrient-poor lakes and ponds	78	69	111
	Nutrient-rich lakes and ponds	174	187	240
	Rivers and streams	289	231	360
Heathland	Total	148	150	206
	Dry heathland	114	142	176
	Dry montane heathland	60	18	64
Lowland grassland	Total	592	571	723
	Dry acid grassland	197	196	252
	Dry calcareous grassland	211	285	320
	Neutral damp grassland	263	233	327
	Neutral pastures and meadows	366	335	451
Marsh and fen	Total	290	272	365
	Acid fens, flushes, mires and springs	132	157	198
	Base-rich fens, flushes, mires and springs	185	165	243
Native pinewood and juniper scrub	Total	50	94	106
	Conifer pinewood and juniper scrub	50	94	106
Rock outcrops, cliffs and screes	Total	173	209	247
	Inland rocks and scree	108	160	168
	Montane rocks and scree	80	56	104
Upland grassland	Total	167	166	884
	Montane acid grassland	133	137	186
	Montane calcareous grassland	63	43	76

1.3.3 Coverage of indicator species

The development of the NPMS indicator species lists included a selection of positive and negative indicator species, with these being chosen in relation to specific habitats. These were largely based on the JNCC Common Standards Monitoring species for equivalent habitats, along with some expert-led additions (see Pescott *et al.* 2014b). Although there can be no scientific definition of 'positive' and 'negative' indicators, given that these are value judgements, these are typically species that are considered by conservationists to represent desirable or undesirable states of semi-natural habitats, where desirable states are those that are associated with a higher abundance of more typical species (i.e. those that are considered to be representative of the habitat type under consideration, where the habitat type is likely to be defined in terms of the NVC; e.g. see http://jncc.defra.gov.uk/page-4259). This means that weedy species that are likely to be indicative of eutrophication, or invasive alien species, have typically been selected as negative indicator species within the NPMS framework.

To reliably detect changes in trends over time for species and habitats, a rule of thumb of 30 records per species was formulated (see section 2.1 for the details behind this decision). Here we present the number of indicator species with at least 30 records per year within each habitat category. These data give an indication of the habitat categories for which it is likely that changes in species' trends may be detectable.

Across the UK and Channel Islands, for eight of the 11 broad habitat categories, there was at least one indicator species recorded in 30 plots in both 2015 and 2016. Native pinewood and juniper scrub and Rock outcrops, cliffs and screes had no indicator species recorded with at least 30 records in either year; Marsh and fen had no indicator species with at least 30 plot records in 2016. Of the 28 fine habitat categories, ten habitat categories had at least one indicator species recorded with 30 plots in both 2015 and 2016, two had at least one indicator species recorded with 30 plots for only one year and 16 had no indicator species recorded with 30 plots in either years. Table 6 presents the number of indicator species with at least 30 plot records broken down by broad and fine habitat category.

Table 6. Number of indicator species with at least 30 plot records per year for each habitat category. The total given for each broad habitat category includes plots recorded only at the broad habitat level (which are not accounted for under the fine habitat totals). The indicators are divided into negative indicators (neg), positive indicators (pos) and all indicators (total). Habitat categories with species recorded in at least 30 plots in both years are highlighted in green, those with species recorded in at least 30 plots in one year are highlighted in orange and those with no species recorded in at least 30 plots in both years are highlighted in red.

NPMS broad habitat category	NPMS fine habitat category	Number of species with ≥ 30 plot records					
		2015			2016		
		neg	pos	total	neg	pos	total
Arable field margins	Total	3	1	4	3	0	3
	Arable field margins	3	1	4	3	0	3
Bog and wet heath	Total	1	8	9	1	11	12
	Blanket bog	0	0	0	0	2	2
	Raised bog	0	0	0	0	0	0
	Wet heath	0	4	4	0	3	3
Broadleaved woodland	Total	5	21	26	5	25	30
	Dry deciduous woodland	3	6	9	3	5	8
	Hedgerows of native species	3	8	11	3	12	15
	Wet woodland	2	1	3	2	0	2
Coast	Total	0	3	3	0	8	8
	Coastal saltmarsh	0	0	0	0	1	1
	Coastal sand dunes	0	0	0	0	0	0
	Coastal vegetated shingle	0	0	0	0	0	0
	Marchair	0	0	0	0	0	0
	Maritime cliff tops and slopes	0	0	0	0	0	0
Freshwater	Total	0	2	2	0	3	3
	Nutrient-poor lakes and ponds	0	0	0	0	0	0
	Nutrient-rich lakes and ponds	0	0	0	0	0	0
	Rivers and streams	0	0	0	0	0	0
Heathland	Total	1	4	5	1	5	6
	Dry heathland	0	3	3	1	5	6
	Dry montane heathland	0	0	0	0	0	0
Lowland grassland	Total	9	19	28	9	27	36
	Dry acid grassland	0	0	0	0	0	0
	Dry calcareous grassland	2	0	2	4	2	6
	Neutral damp grassland	2	2	4	3	3	6
	Neutral pastures and meadows	2	5	7	4	5	9
Marsh and fen	Total	1	1	2	0	0	0
	Acid fens, flushes, mires and springs	0	0	0	0	0	0
	Base-rich fens, flushes, mires and springs	0	0	0	0	0	0
Native pinewood and juniper scrub	Total	0	0	0	0	0	0
	Native pinewood and juniper scrub	0	0	0	0	0	0
Rock outcrops, cliffs and screes	Total	0	0	0	0	0	0
	Inland rocks and scree	0	0	0	0	0	0
	Montane rocks and scree	0	0	0	0	0	0
Upland grassland	Total	0	1	1	0	1	1
	Montane acid grassland	0	0	0	0	0	0
	Montane calcareous grassland	0	0	0	0	0	0

As there were low numbers of fine habitat categories with at least 30 plot records for indicator species in both years for both the UK and the Channel Islands, the following country summaries present coverage of indicator species broken down only to broad habitat categories. The Channel Islands and Northern Ireland had no broad habitat categories with an indicator species recorded in at least 30 plots and the remaining countries had variable numbers of habitat categories well represented by indicator species. Across England, Scotland and Wales, there was consistently at least one indicator species with 30 plots in both 2015 and 2016 in broadleaved woodland and lowland grassland.

Channel Islands

There was only one monad and five plots surveyed in the Channel Islands in 2015 and 2016 and so there were no indicator species recorded in at least 30 plots.

England

Seven of the 11 broad habitat categories had at least one indicator species recorded in at least 30 plots in both 2015 and 2016, one habitat category had one indicator species recorded in at least 30 plots in 2015 but not in 2016 and three habitat categories had no indicator species recorded in at least 30 plots in both 2015 and 2016 (Table 7). Given the survey structure of the NPMS, broad habitat categories with indicators recorded in at least 30 plots in both 2015 and 2016 are more likely to be able to detect changes in trends. The broad habitat categories with the largest number of indicator species with 30 or more plot recordings were broadleaved woodland and lowland grassland.

Table 7. Number of indicator species with at least 30 plot records per year for each broad habitat category in England.
The indicators are divided by negative indicators (neg), positive indicators (pos) and all indicators (total). Habitat categories with species recorded in at least 30 plots in both years are highlighted in green, those with species recorded in at least 30 plots in one year are highlighted in orange and those with no species recorded in at least 30 plots in both year are highlighted in red.

NPMS broad habitat category	Number of species with ≥ 30 plot records					
	2015			2016		
	neg	pos	total	neg	pos	total
Arable field margins	3	1	4	3	0	3
Bog and wet heath	0	2	2	0	2	2
Broadleaved woodland	4	19	23	4	21	25
Coast	0	2	2	0	1	1
Freshwater	0	2	2	0	2	2
Heathland	1	3	4	1	2	3
Lowland grassland	7	12	19	7	16	23
Marsh and fen	1	0	1	0	0	0
Native pinewood and juniper scrub	0	0	0	0	0	0
Rock outcrops, cliffs and screes	0	0	0	0	0	0
Upland grassland	0	0	0	0	0	0

Northern Ireland

Northern Ireland had no habitat categories with an indicator species recorded in at least 30 plots in either year.

Scotland

Three of the 11 broad habitat categories had at least one indicator species recorded in at least 30 plots in both 2015 and 2016; one habitat category had one indicator species recorded in at least 30 plots in 2016 but not in 2015; and seven habitat categories had no indicator species recorded in at least 30 plots in both 2015 and 2016 (Table 8).

Table 8. Number of indicator species with at least 30 plot records per year for each broad habitat category in Scotland.

The indicators are divided by negative indicators (neg), positive indicators (pos) and all indicators (total). Habitat categories with species recorded in at least 30 plots in both years are highlighted in green, those with species recorded in at least 30 plots in one year are highlighted in orange and those with no species recorded in at least 30 plots in both year are highlighted in red.

NPMS broad habitat category	Number of species with ≥ 30 plot records					
	2015			2016		
	neg	pos	total	neg	pos	total
Arable field margins	0	0	0	0	0	0
Bog and wet heath	0	2	2	0	5	5
Broadleaved woodland	2	0	2	2	0	2
Coast	0	0	0	0	0	0
Freshwater	0	0	0	0	0	0
Heathland	0	0	0	0	1	1
Lowland grassland	0	2	2	2	4	6
Marsh and fen	0	0	0	0	0	0
Native pinewood and juniper scrub	0	0	0	0	0	0
Rock outcrops, cliffs and screes	0	0	0	0	0	0
Upland grassland	0	0	0	0	0	0

Wales

Two of the 11 broad habitat categories had at least one indicator species recorded in at least 30 plots in both 2015 and 2016; nine habitat categories had no indicator species recorded in at least 30 plots in either 2015 or 2016 (Table 9).

Table 9. Number of indicator species with at least 30 plot records per year for each broad habitat category in Wales.

The indicators are divided by negative indicators (neg), positive indicators (pos) and all indicators (total). Habitat categories with species recorded in at least 30 plots in both years are highlighted in green and those with no species recorded in at least 30 plots in both year are highlighted in red

NPMS broad habitat category	Number of species with ≥ 30 plot records					
	2015			2016		
	neg	pos	total	neg	pos	total
Arable field margins	0	0	0	0	0	0
Bog and wet heath	0	0	0	0	0	0
Broadleaved woodland	3	1	4	3	1	4
Coast	0	0	0	0	0	0
Freshwater	0	0	0	0	0	0
Heathland	0	0	0	0	0	0
Lowland grassland	1	2	3	1	1	2
Marsh and fen	0	0	0	0	0	0
Native pinewood and juniper scrub	0	0	0	0	0	0
Rock outcrops, cliffs and screes	0	0	0	0	0	0
Upland grassland	0	0	0	0	0	0

1.4 Quality assurance of field survey

Quality assurance (QA) is a key component of ecological monitoring because it allows organisers to understand potential errors and biases, and to take them into account when analysing and interpreting results. Not all errors and biases will have a significant effect on all scheme results, particularly if there is a large sample size, and (when considering trend analyses) if biases are consistent over time.

The NPMS has design features that may help to reduce bias, for example, there are three levels of recording suitable for participants with different plant ID skills. However, as with any recording scheme, some errors and biases remain.

This section describes the main likely sources of error and bias in the NPMS dataset, including plot relocation errors, variation in volunteer expertise, species visual appearance, ease of identification, habitat characteristics, survey timing and intensity, and making estimates of abundance.

The report describes four tests on how to quantify potential errors caused by plot relocation accuracy, rates of misidentification and overlooking, accuracy of cover estimates and survey timing and intensity. These QA tests described here could be carried out in future years to calibrate the dataset and its degree of confidence.

The NPMS covers a large number of species of differing detectability and ease of identification and involves recorders with a wide range of expertise. This can lead to misidentification (i.e. false-positives or Type-I errors) and overlooking (i.e. false-absences or Type-II errors) (Groom & Whild 2017; Morrison 2016). Quality assurance (QA) is a key component of ecological monitoring because it allows scheme organisers to identify and quantify errors and biases, thereby allowing the validity of the findings to be assessed and improving overall confidence in the results.

It is acknowledged that there is always going to be some level of error in survey outputs; QA studies have shown that even in professional monitoring schemes such as the Countryside Survey (CS; Scott *et al.* 2008) and the Environmental Change Network (ECN; Scott & Hallam 2002) there has been a level of under-recording amongst field teams (when compared to QA experts), with knock on effects for ecological interpretation of the results (Scott *et al*. 2008). The key is to understand potential errors and biases, to try to minimise them through good scheme design, and to take them into account when analysing and interpreting results.

Here we discuss the main sources of error and bias within the NPMS and suggest how a QA exercise might be used to address their significance in the future.

1.4.1 Sources of error

Relocation errors
Because NPMS plots are not permanently marked, accurate relocation relies on the documentation of locations; this includes a mixture of sketch maps, GPS coordinates, photographs and site descriptions, as well as personal knowledge. This inevitably leads to a degree of relocation error, especially where plots occur in homogeneous stands of vegetation with few notable features (e.g. open grasslands, moorlands *etc*.), on the edge of features that might change position over time (e.g. arable field margins, fluctuating shorelines, outgrowth of hedgerows *etc*.) or in dense vegetation that is difficult to navigate around (e.g. woodland on steep terrain). Error rates are also likely to be higher where plots

are relocated by surveyors unfamiliar with the plot locations (e.g. when a square is passed on to a different surveyor). Relocation using GPS coordinates is also susceptible to error due to low precision: GPS signals can be poor in woodlands and gorges or on steep terrain where slight inaccuracies are magnified. The importance of such errors may vary with the research application; for example, the impacts of plot relocation errors on species detectability may be more important in other applications than in the use of NPMS data for ground truthing Earth Observation (EO) data (e.g. section 3.5), particularly if the scale of the EO data being checked is coarser than the relocation error.

Volunteer expertise
Participation in the NPMS is open to botanists of all abilities, and consequently, there is inter-observer variation in species and habitat identification and in general recording expertise. To some extent these issues are minimised by using a structured (standardised) method which excludes difficult to identify species from the Wildflower list and Indicator species lists. However, there may be a further issue if volunteers are not able to identify the habitat they are recording in and therefore correctly identify the set of target species they should be looking for. This may be a more complicated problem as habitat identification skills may not correlate well with plant identification skills (i.e. botanical experts are not always good at identifying habitats). These difficulties are likely to be greatest for habitats in remote regions that require specialist knowledge and expertise (e.g. coastal habitats, heathlands, mires, bogs, and montane communities).

Visual apparency
Species vary considerably in terms of their visual apparency (size, colour, period of flowering/leafing, *etc*.). As a general rule, larger plants with bright flowers, longer flowering periods and perennial life-histories are more likely to be recorded than small, short-lived species with dull flowers. Perennial geophytes are an obvious exception due to the long periods of aestivation below ground. For all these reasons, there is likely to be a taxonomic bias within NPMS in terms of the species that are likely to be overlooked or misidentified.

Ease-of-identification
The ease by which species can be identified varies enormously and this can lead to major sources of bias or error in monitoring schemes, especially where common species which dominate communities are confused (e.g. *Festuca ovina* versus *F. rubra*). We attempted to reduce this source of error in NPMS by excluding difficult-to-identify species from the Wildflower and Indicator species lists. However, errors are still likely to occur as even experts will have groups of species that they are less familiar with, and vegetative identification of grasses and sedges can often be challenging even to experts if the skills are not regularly refreshed.

Habitat characteristics
Some habitats are more challenging to identify because the distinctions between similar habitats require specialist knowledge or a high degree of botanical ability. This is particularly the case with for many wetland habitats which often dominated by more challenging species groups such as sedges, aquatic plants, *etc*. So, as with species, there is likely to be a habitat bias in terms of the accuracy of the data within the NPMS.

Survey timing and intensity
Plant species vary in their detectability throughout the year (due to phenology; see 'Visual apparency' above) and so the timing of visits to record NPMS squares will clearly have an influence on the species recorded, as well as potentially estimates of change if plots are revisited at different times of the year (note that the NPMS instructions encourage surveyors to spread their visits out in the season, in order to maximise the chances of detecting species). Clearly, the number of visits in any one year and amount of time spent surveying (survey intensity) will also influence the results (but see also section 2.5.5 below). Table 10

demonstrates this, as well as how this is dependent on the survey level. There are more unique single-sample detections at higher levels, especially at Inventory level, no doubt because surveyors are seeking and recording more species in general. The ratio of non-detections to detections, however, drops with survey level, presumably because of the increasing skill level of the surveyors. Amongst other things this suggests that averaging cover values between visits within a year is likely to be a misleading strategy compared to taking the maximum cover value across visits. It also suggests that species are considerably more likely to be completely missed (Type-II error) at the Wildflower level.

Table 10. Taxon within-plot detection levels for 2016.
For the 2016 survey season, this table gives counts of the number of times taxa were recorded either in one of two samples, or in two of two samples. Plots that were surveyed only once, or more than twice, were excluded.

Survey Level	(i) Number of times a taxon was detected in both plot samples	(ii) Number of times a taxon was detected in only one of two plot samples	ii/i
Wildflower Survey	956	900	0.94
Indicator Survey	2429	1050	0.43
Inventory Survey	6004	2342	0.39

Estimates of abundance
The estimation of abundance using ordinal scales can vary dramatically between recorders and at different times of the year. This will, to some extent, have been reduced by the use of abundance categories in the NPMS but, even so, inter-observer differences are still likely to be significant.

1.4.2 Options for QA assessment of the NPMS

Test 1: Plot relocation accuracy
This test would aim to quantify the impact of plot relocation accuracy on species composition and abundance, ideally across all NPMS fine-scale habitats, with sufficient replication within each to perform statistical tests. This could be achieved by re-locating a random sample of plots within each fine-scale habitat using the documentation provided (with or without GPS, photographs *etc*.) and recording species composition and abundance without any prior knowledge of the plot location or composition. The 'actual' position of the plot would then be marked out and the composition of the plot re-recorded by the same surveyor. Differences between the two surveys and the original would then be assessed in relation to expertise of the original surveyor, habitat type, information available to relocate etc. The survey would be carried out by an 'expert' to ensure that the plots are comprehensively surveyed.

Test 2: Rates of misidentification and overlooking
The aim of this test would be to quantify the rates of misidentification and overlooking in relation to recorder expertise and habitat. This test could be based on a subset of the samples re-recorded for Test 1 and would be carried out approximately the same time as the original survey (i.e. within a few days of routine NPMS recording). Tests would be based on the re-sampling of the 'actual' plots as described above. Initially plots would be recorded 'blind' by an expert. Habitat categories and lists of species recorded in both surveys would then be compared, and any species missed would be searched for again. Ideally, the sample would include plots recorded by recorders with a range of expertise.

Test 3: Accuracy of cover estimates
Variation in cover estimation could be quantified across the sample plots used in Test 2. Following the expert survey, botanists with a range of abilities would quantify the cover of

species known to occur in each plot. Comparisons in cover values would then be compared in relation observer expertise, species traits etc. Ideally this test should be carried out across a range of NPMS habitats.

Test 4: Survey timing and intensity
The effect of survey timing and intensity could be assessed by monitoring a subsample of the plots re-surveyed in Tests 2-3. Plots would be monitored monthly to assess how (a) timing and (b) the number of visits influenced the species recorded and estimates of species cover. Ideally this would be recorded across a range of NPMS habitats although this is unlikely to occur given the large number of survey visits required.

2 Analysing status and trends

2.1 Power analyses: Reviewing the current data resource

This section summarises key findings of Pescott *et al*. (2016), an investigation into different approaches to assessing trends in relation to the NPMS. Pescott *et al*. (2016) recommended the use of hierarchical models for plant monitoring schemes, which can be applied in a Bayesian context. This approach can bring greater realism and sensitivity to measures of population change, and can also make use of interval censored data, and so makes use of data on species abundance categories from plots. This section summarises the approach, and outlines further recent developments to it, for example by Irvine *et al*. (2016).

An important 'rule of thumb' from this work is that a minimum of 30 sampling points where a species is recorded is needed to allow trend detection with reasonable confidence (see section 1 above for coverage data). The first two years of NPMS data suggest that with current levels of survey, percentage cover trends over time can be measured for around 150 of the indicator species and a further 70 non-indicator species or species groups. If we want to obtain trends by habitat, by country, or by habitat country combination, then 30 sample points within a data subset would be required. This means there is a lower number of species for which we can obtain trends within these categories. Details are given in an annex to this report (see below), providing information on both what the NPMS outputs will be able to show, and indicating where further sampling effort needs to be targeted to increase the range of possible outputs.

2.2 Earlier conclusions from NPMS reports and Pescott *et al*. (2016)

2.2.1 Introduction

Pescott *et al*. (2016) provide the following summary of power analyses in the context of environmental monitoring:

Conducting an appropriate power analysis for a monitoring scheme involves deciding on a set of relevant scenarios to investigate, covering a range thought plausible once the proposed scheme is established. Important variables affecting the quality of inference include those that represent the underlying structure of the data, e.g. the number of years of monitoring, the number of sites monitored or the arrangement of repeated site visits in time and space (Urquhart 2012), and those that represent the hypothetical effect that the monitoring is intended to capture, e.g. changes in species' abundances or distributions within a specified time frame, which may be a constant change of a fixed number of organisms or area of cover per year, or a proportional change in such a measure. Temporal trends, of course, may also vary across sites. Simple, mathematically-explicit estimates of power are not available in such multi-faceted studies, but, in a classical framework, simulation-based approaches to power analysis (Bolker 2008; Gelman & Hill 2007) have meant that ecologists have increasingly had a greater ability to capture the complex generating processes that often characterise data collected by monitoring schemes. These include the possibility of modelling variation in trends over time at different sites through the use of mixed models (Gelman & Hill 2007; Johnson *et al*. 2015; Miller & Mitchell 2014). These approaches should help to ensure that the results obtained embody a greater realism; this may be particularly important for monitoring schemes, which often cover large geographic areas across which the drivers of change for particular species or habitats may vary. The inclusion of greater flexibility in the modelling of spatially-varying structures in power analyses is therefore likely to ensure that decisions made regarding the inauguration and funding of particular monitoring schemes are better informed (Miller & Mitchell 2014), and may also help to avoid unrealistic expectations."

An additional complication is that NPMS surveyors collect interval-censored plant cover data, i.e. observations about plant cover are collected according to an ordered categorical scale in order to reduce time in the field, and to reduce the potential for discrepancies between surveyors (Irvine & Rodhouse 2010). Several of such plant cover scales are in use around the world (Peet & Roberts 2013), although variations on the 'Domin' scale predominate in Britain (e.g. Rodwell 1991). Pescott *et al*. (2016) explore four types of model for this data type, although other types are possible (e.g. see https://peerj.com/preprints/2532v1/#feedback and Irvine *et al*. 2016). The initial NPMS technical report (Pescott *et al*. 2014a) focused on a Bayesian model that was considered to be the most sophisticated in modelling per species plant cover data collected according to interval-censored cover scales, whilst also allowing for complex hierarchical variance structure in the data (Model 4 of Pescott *et al*. 2016); this review deals with the NPMS data to date in light of this model.

For completeness we note here that, subsequent to the review of Pescott *et al*. (2016), additional models have been published that use a similar Bayesian formulation to ours, most notably that of Irvine *et al*. (2016), and that our attention has been drawn to additional possibilities to those considered by our reports (e.g. mixed model approaches to ordinal regression; see https://peerj.com/preprints/2532v1/#feedback). The model of Irvine *et al*. (2016) extends, and arguably improves upon, the logic of our Bayesian model by allowing for the probability distribution underlying the hierarchical Bayesian model to take the form of a zero-augmented beta distribution. The beta distribution has been noted as being particularly well-suited to plant cover data by several authors (see cited authors in Irvine *et al*. 2016), and the zero-augmented form of this distribution further extends this suitability by allowing models to potentially distinguish between environmental covariates driving presence/absence and abundance. The utilisation of such models may produce different insights to simpler formulations (Irvine *et al*. 2016); however, the implications of these extensions for Type I errors (false positives) and Type II errors (false negatives) in relation to other models, such as our Bayesian hierarchical model for censored data (i.e. Model 4 of Pescott *et al*. 2016) have not yet been assessed.

2.2.2 Power estimates from Pescott *et al*. (2016)

Pescott *et al*. (2016) focused on several different simulated scenarios of change, including different numbers of sites, different initial starting percentage plot covers, and different levels of percentage cover decline over a ten-year period. Variance parameters (e.g. variance in a single species' trend across sites) were not varied, although they were empirically informed through modelling of the long-term Countryside Survey (CS) dataset. The approach to summarising inferences from the Bayesian model was not identical to a classical (i.e. frequentist) approach to power, but instead focused on summarising across the posterior distributions of the multiple estimates of a temporal slope parameter (i.e. that determining the trend over time). The simulated data included a known rate of decline, and therefore a successful (i.e. true positive) model run should identify the trend as being negative. By running 100 simulations for each scenario, a Bayesian analogue to power was created by storing the percentile of each posterior distribution of the 100 slope parameters that was at zero: e.g., if the entire distribution was below zero, the percentile would be 100, if the posterior was equally distributed either side of zero, then the percentile would be 50. This is a way of indicating the strength of our belief in a negative slope provided by the dataset; given that the datasets were simulated to have a true underlying negative trend, a higher average percentile across the simulated datasets indicates a stronger belief in the trend. This can be considered similar to statistical power, where power is the long-run frequency of correctly rejecting a null hypothesis (of no trend), when there truly is no trend.

This Bayesian approach to power results in smoother increases in the simulated negative trend, compared to using the frequentist approach (Pescott *et al*. 2016). This is because frequentist power is often based on the arbitrary selection of a *P*-value of 0.05 (α) as the level at which to reject the null hypothesis; therefore, there will typically be a zone of rapid increase in power as scenario parameters pass through sets of data that produce borderline significant results. The Bayesian summary method incorporates the gradual increase in the believability of a trend, resulting in much more gradual 'power' curves (Pescott *et al*. 2016). As another example of the differences between the methods, note the difference between 50% power and the 50% level of belief for the Bayesian analyses (Pescott *et al*. 2016): although 50% power means that the null hypothesis will be correctly rejected half of the time, for an average belief of 50% in a negative trend, then the result for a single dataset providing evidence for a decline will typically be weak. This makes more sense to us as a summary of the information contained within an analysis of a single dataset, as opposed to a binary accept/reject decision.

Given this gradual change in the believability of a negative trend shown by our Bayesian model of the simulated scenario-based datasets, there are only small differences in the 'power' graphs produced for this model (Figure 3 below; reproduced from Pescott *et al*. 2016). Even the smallest initial percentage plot cover (5%), the smallest annual proportional decline (4.5% per annum, equivalent to an overall decline of 30% over 10 years), and 30 sites (i.e. plots) result in a greater belief in a decline than in an increase (with the average across simulations being higher than 60% around year 4 [the actual figures across simulations were 57% in year 3 and 64% in year 5]; top left panel, Figure 3). Therefore, in the subsequent sections, we summarise those Indicator and Inventory species (see Annex 1 below) reaching or exceeding the 30-plot threshold in 2015 and 2016 combined, also subdivided by country.

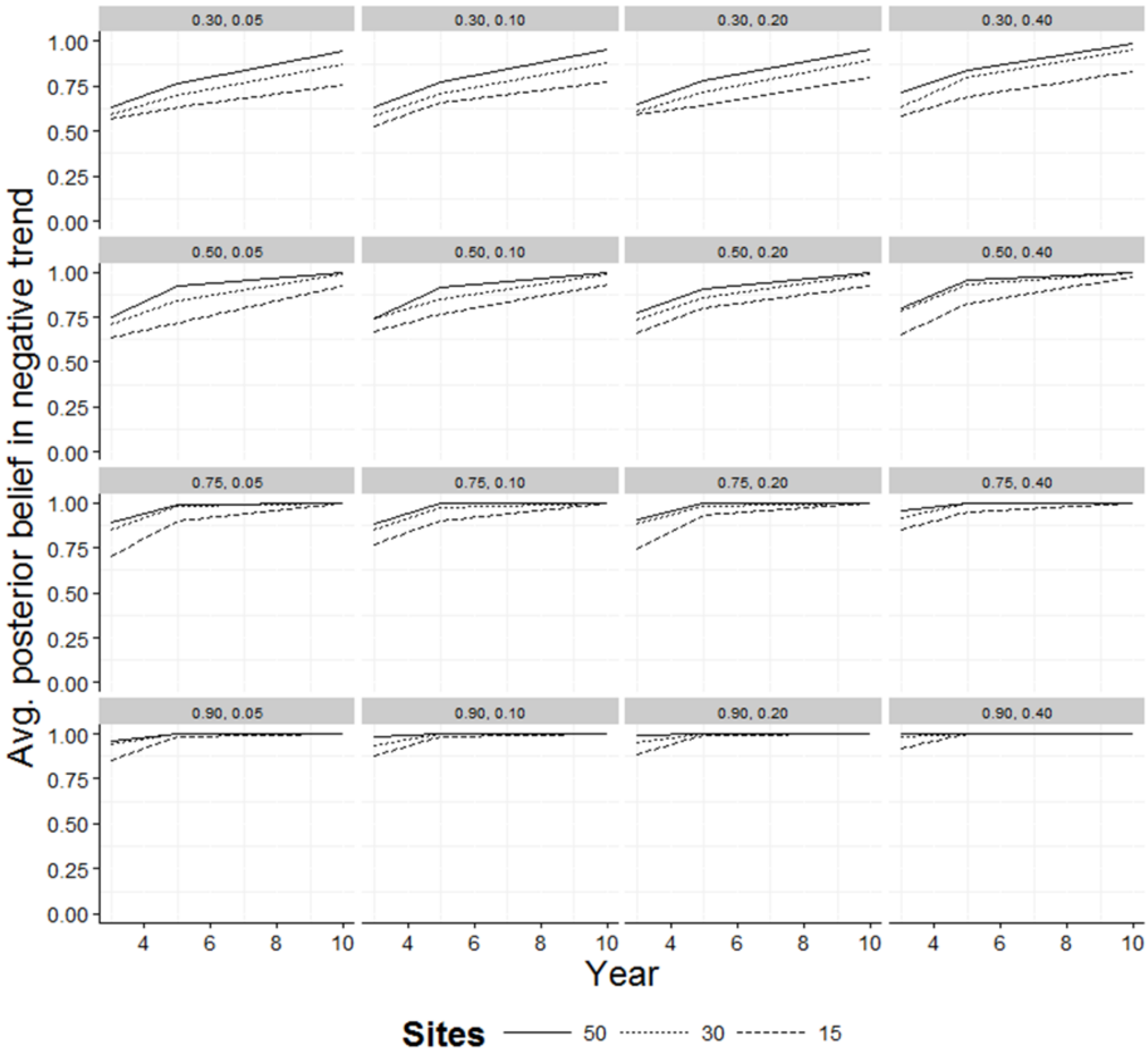

Figure 3. The average belief (proportion of the posterior distribution for the slope coefficient below zero) in a negative trend across 100 simulations from an interval-censored hierarchical Bayesian regression.
Rows represent different proportional declines undergone over a 10-year period (the first number given in the individual graph headers). Columns (the second number given in the individual graph headers) represent different initial starting proportional covers.

2.2.3 Conclusions

Species-level analyses identified a requirement of 30 unique plots as a rule-of-thumb for having a reasonable belief in a decline when using the Bayesian regression model described in Pescott *et al*. (2016). It is worth noting that power analyses conducted for the BTO/JNCC/ RSPB Breeding Bird Survey have also suggested that around 30 samples per species are required for reporting trends at the national level (R. Robinson, BTO, pers. comm.) Annex 1 provides summaries of the taxa that have been detected in at least 30 unique plots.

However, in this context several points should be noted:

- The Bayesian 'interval-censored' model of Pescott *et al*. (2016) was based on the assumption that a species' occurrence percentage cover values are transformed and modelled on the logit-normal scale (Irvine and Rodhouse 2010). This means that zero values are actually assigned to arbitrarily small cover values (see Table 1 in Pescott *et al.* 2016). Recent improvements on this method using 'zero-augmented' approaches could now offer alternative models for these data types (Irvine *et al*. 2016).

- The overview presented here is across NPMS habitats. Clearly, for any habitat-specific trend, the numbers of available plots would often be lower for any particular species (see section 1.3 above).
- The power analysis of Pescott *et al*. (2016) did not consider the power of other possible approaches to summarising the data; for example, trends in overall species richness or the number of indicator species. (Pescott *et al*. (2014) did consider power for trends aggregated across species, but this was only done for a generalised linear mixed model using cover-interval mid-points; however, the conclusions from this work highlighted general patterns that apply to any model.) We note that power for species richness-based indicators (i.e. count data) is, generally speaking, far more straightforward than power for interval-censored data, with many 'off-the-shelf' solutions available (e.g. Johnson *et al*. 2015).

2.3 NPMS data and habitat quality: An overview

Whilst being able to assess trends in individual species can be useful, it is particularly worth considering how changes in positive and negative indicator habitats can provide extra information for assessing habitat condition. This section investigates some of the selection criteria for NPMS indicators. The analysis presented here shows that the species richness measures are, in most habitats, highly correlated (either positively or negatively) with the habitat condition score, and hence could be used as indicators of habitat condition. However, as the relationship is not straightforward, and some habitats show no correlation, further refinement, analysis and interpretation is required.

The assessment of the quality of 'features' on sites, whether habitat, species, or geological, is the main purpose of the Commons Standards Monitoring (CSM) framework of the Joint Nature Conservation Committee (JNCC 2004). JNCC (2004), quoting Brown (2000), define monitoring as "an intermittent (regular or irregular) series of observations in time, carried out to show the extent of compliance with a formulated standard or degree of deviation from an expected norm". The Common Standards approach to site monitoring is based upon attributes ("characteristics of an interest feature that describe its condition, either directly or indirectly"; JNCC 2004) of habitats, selected species groups, or geological features (https://jncc.gov.uk/our-work/common-standards-monitoring-guidance/). The attributes of habitats chosen for CSM have been developed by habitat experts and subsequently refined over time (Williams 2006). Habitat attributes vary according to habitat type, but typically include things such as feature extent, frequency or cover of indicator species, and physiognomic characteristics of vegetation (e.g. JNCC 2009). Full plot data, *i.e.* comprehensive quadrat data, are not normally required—historically this approach has generally been considered to be too resource intensive to be implemented across all Sites of Special Scientific Interest (SSSIs) containing a habitat feature, hence the current focus on attributes, or indicators within CSM (Rowell 1993).

The NPMS has aimed to have a joint focus on species and habitats from its inception; indeed, an early scoping report tasked with investigating the options for a national plant monitoring scheme discussed a number of indicators of habitat quality, many of which have been incorporated into the current scheme (Walker *et al*. 2010a). The information recorded for each plot, in addition to species' cover scores, is intended to contribute to our understanding of why the quality of semi-natural habitat in a particular monad may be changing over time, in order to indicate the local pressures and drivers of change. The additional attributes recorded by volunteers are: habitat type, aspect, slope, vegetation height (a four-point percent-cover scale against five height categories), management (type and description), how wooded the plot is (four descriptive options including hedgerow), grazing pressure (low, moderate, high) and by which animals (see www.npms.org.uk/content/resources for a PDF of the survey form and guidance). Alongside species' cover values, bare soil, bare rock/gravel, litter and "moss & lichen" cover assessments are also requested. This information is collected for each visit. Plot photos and general comments (e.g. of tree health) are also encouraged.

CSM indicator information was incorporated into the selection of NPMS indicators, particularly for the choice of negative indicators (Pescott *et al*. 2014b). The NPMS indicators that are also CSM indicators are presented here in online Appendix 3. Online Appendix 4 also provides the positive or negative 'status' of each NPMS Indicator species per habitat. Pescott *et al*. (2019) provide an overview of the selection of indicator species within the NPMS, as well as an assessment of how well the chosen Wildflower and Indicator species capture known ecological gradients within British and Irish plant communities.

2.3.1 Plot data and indicators of habitat quality

Within a separate project, Maskell and Smart (2016) investigated how metrics of quality used within JNCC Common Standards Monitoring (CSM) guidance and the Natural England Higher Level Stewardship Farm Environment Plan (FEP) assessment were associated with other possible metrics, such as species richness or the richness of positive indicators. Maskell and Smart (2016) compiled habitat-specific indicators of quality from these guidance documents, creating checklists of attributes for the following habitats: blanket bog, lowland grassland, heathland, and acid grassland (adapted for Table 11 below). Data collected through the Welsh Glastir Monitoring and Evaluation Programme (GMEP) field survey were used to derive quality scores for these habitats. This was done both according to summing the number of "passed" attributes from the derived habitat checklists (from which Table 11 is adapted) and according to individual condition measures derived from actual vegetation plot or field mapping data. At the same time, other metrics were also calculated, including vegetation plot indicator richness values created using NPMS indicator lists and total species richness. The attributes derived from the vegetation plots were subject to a Principle Components Analysis (PCA) ordination, with the checklist condition score, total species richness, NPMS Wildflower species richness, and other condition metrics derived from the GMEP mapping data projected onto the ordinations passively. The aim was to investigate the relationship between a set of "reduced" approaches to habitat quality, and the full set of habitat-specific CSM attributes as derived from full vegetation plot data. An example of this approach for blanket bog is provided below in Figure 4 (taken from Maskell & Smart 2016).

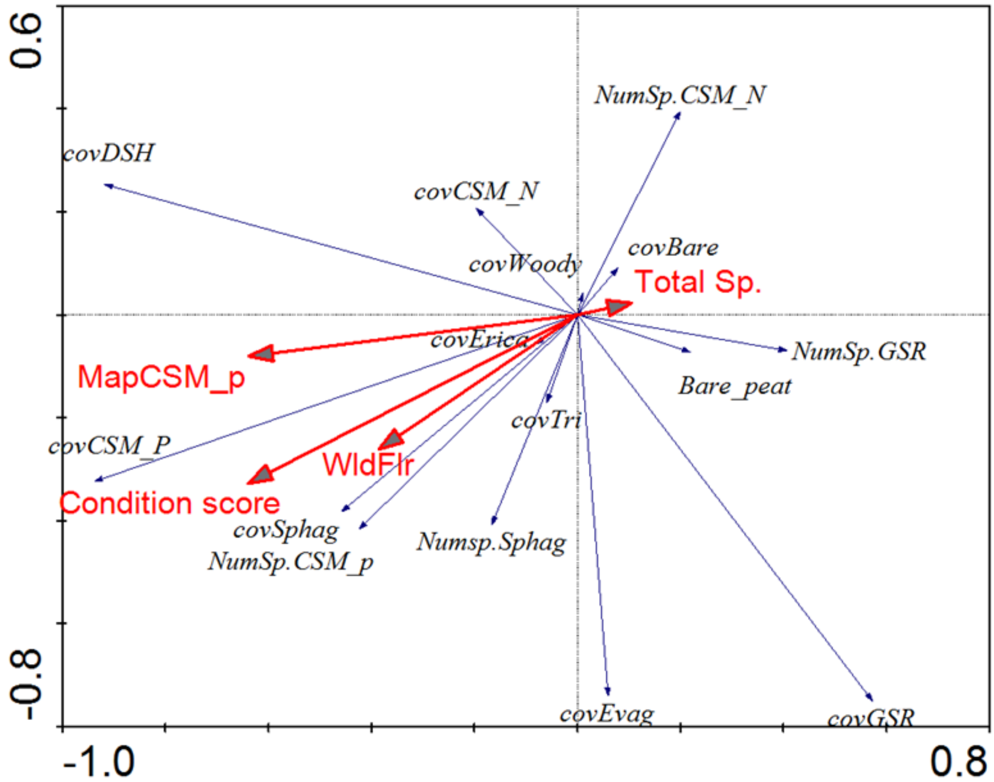

Figure 4. A Principle Component Analysis of (standardised, centred) plot condition measures for blanket bog (attributes in black text).
The red attributes were projected passively onto the ordination. From 12 o'clock (black text): NumSp.CSM_N = Number of positive CSM indicators from vegetation plot data; covBare= Cover of bare ground in vegetation plot; NumSp.GSR = Number of Grass, Sedge or Rush species; Bare_peat = % of bare peat in mapped parcel; covGSR = Cover of Grass, Sedge or Rush species; covEvag = Cover of Eriophorum vaginatum; covTri = Cover of Tricophorum cespitosum s.l.; NumSp.Sphag = Number of Sphagnum species; NumSp.CSM_p = Number of positive CSM indicators from vegetation plot data; CovSphag = Cover of Sphagnum species; covErica = Cover of Erica species; covCSM_P = Cover of positive CSM indicators from vegetation plot data; covDSH = Cover of Dwarf Shrubs; covCSM_N = Cover of negative CSM indicators from vegetation plot data; covWoody = Cover of woody species. From 12 o'clock (red text): Total Sp. = Total number of species in a vegetation plot; WldFlr = Number of Wildflower level indicators recorded in NPMS; Condition score = Total score calculated from number of pass/fails for each condition variable (see Table 11); MapCSM_P = Number of positive CSM indicators from GMEP mapping data.

One of the main conclusions from this work was that the correlation between measures of indicator richness, including NPMS Wildflower level data, and the checklist approach to attributes, varies according to habitat. For example, for blanket bog (Figure 4), species-based indicator measures (number of NPMS Wildflower species, number of CSM positive indicators in the parcel surveyed), were highly correlated with the 'Condition score' created from the CSM attribute checklist for the habitat. However, in other habitats this was not the case: for example, for lowland grassland, the derived condition score was strongly negatively correlated with the number (and cover) of CSM positive indicator species in the mapped area, and the number of NPMS Wildflower species. This may be to do with the fact that richer areas (in terms of indicator or overall species richness) were under-managed in the study area, and so fail on structural or broad compositional attributes (e.g. one can imagine *Crataegus*- or *Prunus spinosa*-invaded abandoned grassland), whereas areas that are in better condition according to these broader attributes (Table 11) are those that are actually poorer in terms of species richness.

Similar patterns were present in the other habitats examined (heathland, acid grassland; Maskell & Smart 2016). It is also worth noting here that for all habitats except heathland, there was a strong correlation between the NPMS Wildflower indicators and total species richness. For heathland, total species richness in plots was also negatively correlated with the condition score derived from a similar list of attributes to Table 11, but the NPMS Wildflower indicators were not correlated with either (although they were highly correlated with the number of CSM positive indicators in a plot, indicating that in this habitat, an indicator approach may be a better metric than total richness, but that derived condition scores focusing on more structural attributes may be complementary (due to the fact that variation in these attributes may be largely independent of indicator richness)).

The conclusions from the work of Maskell and Smart (2016) raise a lot of interesting questions that would be valuably investigated using an independent dataset (e.g. an investigation into the Countryside Survey 2007 dataset and the current NPMS dataset could reveal whether the relationships implied by Maskell & Smart 2016 hold).

Table 11. The habitat-specific CSM or FEP metrics used by Maskell and Smart (2016) to create semi-quantitative indices of quality.

These are divided between composition and structural measures. The NPMS evidence that is available for quantifying each metric is also provided alongside.

		Blanket Bog	NPMS		Lowland grassland	NPMS
Vegetation composition	1	At least 6 indicators present	Well-covered by NPMS Indicators	1	2-6 positive indicators (2 frequent, 2 occasional)	Well-covered by NPMS Indicators
	2	50% of cover from 3 indicator species	Well-covered by NPMS Indicators	2	Grass:herb ratio fall within the range 40-90% herb cover	Complicated by use of indicators, but 12 grasses included at Indicator level
	3	Bog-mosses (*Sphagnum* spp.) at least frequent, with less than 10% damaged (dead/bleached or crushed/broken/pulled). *Sphagnum* spp. not only *S. fallax*	Not currently recorded (except as "Mosses and lichens" cover)	3	Large *Carex* spp. (with leaves more than 5mm wide) e.g. *Carex acutiformis,* large grasses (with leaves more than 10mm wide and stout stems) e.g., *Arrhenatherum* and *Dactylis, Glyceria maxima, Phalaris arundinacea, Phragmites australis,* large rushes <30% cover	*Phalaris arundinacea* and large rushes only at Indicator level
	4	Any one of *Trichophorum* spp., *Erica* spp., *Eriophorum vaginatum* should not exceed 75%	All covered by NPMS Indicators	4	Agriculturally favoured species <20% cover	*Holcus lanatus* only at Indicator level
	5	Cover of dwarf shrubs between 20% and 75%	All covered by NPMS Indicators	5	Woody species and bracken together <5% cover	Bracken, *Crataegus*, *Ulex europaeaus* only
	6	Cover of grasses, sedges and rushes less than 75%.	Main species covered by NPMS Indicators	6	<5% agricultural weeds	Weedy species well covered (*Cirsium arvense*, *Rumex* spp., *Urtica*, *Galium aparine*, *Senecio jacobaea*)
	7	Non natives<1%	Non-natives only covered by "Conifer seedlings and saplings" (unless at Inventory level)			
	8	<10% trees and scrub	*Betula* spp. and conifer seedlings covered by NPMS Indicator level. Plot woodedness, plot photos, and vegetation structure (height) also recorded			
	9	<1% negative indicators	*Cirsium arvense*, *Urtica dioica* and coarse *Juncus* spp. included as NPMS negative Indicators			
Structure	10	No burning	Survey form management comments box	7	<5% bare ground	% cover information for bare soil collected
	11	<10% bare ground	% cover information for bare soil collected	8	Litter <25% sward	% cover information for litter collected
	12	Extent of eroding peat < stable peat and new vegetation	Not specifically detailed on survey form, but may be recorded in comments. Plots photos also	9	5-20 cm. In hay meadows, the lower limit is 5 cm, with no upper level.	Vegetation structure information collected
	13	Grazing impacts	Survey form management comments box; specific grazing questions (intensity/animals)			

Table 11 (continued). The habitat-specific CSM or FEP metrics used by Maskell and Smart (2016) to create semi-quantitative indices of quality.
These are divided between composition and structural measures. The NPMS evidence that is available for quantifying each metric is also provided alongside.

		Heathland	NPMS		Acid grassland	NPMS
Vegetation composition	1	>2 indicator heathland species (dwarf shrubs)	Well-covered by NPMS Indicators	1	>2 indicator species	Well-covered by NPMS Indicators
	2	50% cover (dwarf shrubs)	Well-covered by NPMS Indicators	2	>10% forbs	Well-covered by NPMS Indicators
	3	All growth phases of heather present	Not recorded specifically, but partly covered by vegetation structure information and plot photos.	3	<25% *Ranunculus repens* and *Bellis perennis*	Only *Bellis perennis* for Montane acid grassland
	4	Neither dwarf shrubs or graminoids >75% cover (upland wet heath only)	Well-covered by NPMS Indicators (Wet heath)	4	<10% *J. effusus*	NA
	5	*Ulex europaeus* <25%	*Ulex gallii* /*minor* only for NPMS Dry heathland habitat. Plot photos/structure may assist.	5	*Juncus squarrosus* and *Rhytidiadelphus squarrosus* <33%	*J. squarrosus* recorded in Dry acid grassland (lowland)
	6	Non-natives <1%	Only included under Conifer seedlings and saplings in Wet heath at Indicator level	6	Non natives <1%	NA
	7	<10% bracken	Included for Dry heathland	7	Woody species and bracken together <5% cover	Bracken and gorse included for Dry acid grassland (lowland)
	8	<20% trees and scrub	*Betula* spp., *Ulex* spp. and conifers recorded as specified above.	8	<1% negative indicators	Partly covered by NPMS Indicators
	9	<1% negative indicators	Partly covered			
	10	<10% *Juncus effusus*	Wet heath only			
Structure	11	No burning	Survey form management comments box	9	<10% bare ground	% cover information for bare soil collected
	12	<10% bare ground	% cover information for bare soil collected			
	13	Grazing impacts	Specific grazing questions (intensity/animals) on survey form			

2.4 NPMS indicator species and environmental drivers

2.4.1 Background

Changes in the frequency and abundance of NPMS indicator species are intended to help capture patterns in vegetation relating to key environmental gradients and drivers known or suspected to be impacting on biodiversity (e.g. nitrogen deposition, climate change, management intensification or abandonment). However, for many of the NPMS indicator species the relationships with gradients and drivers are poorly known or documented trends are scattered in the scientific literature. In this section we provide a brief review of 13 recent UK studies that have analysed temporal or spatial trends in relation to nitrogen deposition (seven studies), climate change (three studies), abandonment (one study) or multiple drivers (two studies). The studies (Bennie *et al*. 2006; Britton *et al*. 2009; Caporn *et al*. 2016; Duprè *et al*. 2010; Henrys *et al*. 2011; Jones *et al.* 2004; Ross 2015; Ross *et al.* 2012; Stevens *et al*. 2016, 2009; Stroh *et al*. 2017; Van den Berg *et al.* 2011; Walker *et al*. 2009) are more thoroughly documented in the supporting online appendix (see below).

2.4.2 Results

Most of the 13 studies are based on empirical analyses of vegetation datasets, either by revisiting permanently located plots (re-visitation) or through space-for-time substitution approaches. These also include two studies that present reviews of previous studies, including ones already included in this review. Here we present a light review and only include recent studies (post-2000) known to the authors that included trend-driver relationships for NPMS species. A more comprehensive review would have taken into account a much broader body of work, most notably including experimental studies on the impact of drivers.

The results of the review are presented as a spreadsheet in online Appendix 5. This provides details of the studies included and the trends in relation to drivers, direction of response as reported, and habitat, as well as a table overviewing the associations between NPMS indicators and NPMS habitats as background information (see also the metadata sheet provided in online appendix 5). The results presented here provide a brief overview of the data included in the appendix; however, note that these results are direct summaries of the original works, and the inclusion of any particular species/N deposition relationship in this summary should not be taken to imply anything regarding the reliability of this conclusion. For example, increases or decreases for any given species based on *P*-values alone are not a robust basis for meta-analysis (Gurevitch & Hedges 2001).

Nitrogen deposition

Table 12. The number of positive and negative indicators per NPMS habitat where a reviewed study indicated an increase or decrease in response to nitrogen deposition.
Where a species has been documented as both increasing and decreasing in the habitat category in response to nitrogen, it is recorded in both the increase and decrease columns within any given indicator type. The column "Positive/ Negative indicators" covers those species whose status as positive or negative indicators varies by habitat.

NPMS habitat		Positive indicators			Negative indicators			Positive/ Negative indicators		
Broad	**Fine**	**Increase**	**Decrease**	**Total**	**Increase**	**Decrease**	**Total**	**Increase**	**Decrease**	**Total**
Bog and wet heathland	[Habitat at broad scale]	7	16	22	2	0	2	1	0	0
Broadleaved woodland	Dry deciduous woodland	0	4	0	0	1	1	1	1	2
Coast	Costal sand dunes	3	1	3	0	0	0	0	0	0
Heathland	[Habitat at broad scale]	2	1	3	0	0	0	0	0	0
Heathland	Dry heathland	1	0	0	0	0	0	0	0	0
Heathland	Dry montane heathland	0	3	3	0	0	0	1	0	1
Lowland grassland	[Habitat at broad scale]	1	12	13	2	0	2	2	0	2
Lowland grassland	Dry acid grassland	11	11	20	1	0	1	1	1	1
Lowland grassland	Dry calcareous grassland	8	23	29	1	0	1	0	0	0
Upland grassland	Montane calcareous grassland	0	2	2	0	0	0	0	0	0

Climate change

Table 13. The number of positive and negative indicators per NPMS habitat which show an increase or decrease in response to the driver of climate change.
Where a species has been documented as both increasing and decreasing in the habitat category in response to nitrogen, it is recorded in both the increase and decrease columns within any given indicator type.

NPMS habitat		Positive indicators			Negative indicators		
Broad	**Fine**	**Increase**	**Decrease**	**Total**	**Increase**	**Decrease**	**Total**
Heathland	Dry montane heathland	12	7	19	0	0	0
Marsh and fen	[Habitat at broad scale]	12	3	14	1	0	1
Upland grassland	[Habitat at broad scale]	5	3	8	1	0	1
Upland grassland	Montane acid grassland	7	6	13	0	2	2

Abandonment

Table 14. The number of positive and negative indicators per NPMS habitat which show an increase or decrease in response to the driver of abandonment and under-grazing.
Where a species has been documented as both increasing and decreasing in the habitat category in response to nitrogen, it is recorded in both the increase and decrease columns within any given indicator type.

NPMS habitat		Positive indicators			Negative indicators		
Broad	**Fine**	**Increase**	**Decrease**	**Total**	**Increase**	**Decrease**	**Total**
Lowland Grassland	Dry calcareous grassland	6	4	10	0	0	0

Multiple drivers

Table 15. The number of positive and negative indicators which show an increase or decrease in response to multiple drivers (habitat information not provided).
Where a species has been documented as both increasing and decreasing in response to nitrogen, it is recorded in both the increase and decrease columns within any given indicator type. The column "Positive/Negative indicators" covers those species whose status as positive or negative indicators varies by habitat.

Positive indicators			Negative indicators			Positive/Negative indicators		
Increase	**Decrease**	**Total**	**Increase**	**Decrease**	**Total**	**Increase**	**Decrease**	**Total**
9	36	45	7	1	8	1	2	3

2.4.3 Conclusions

The positive and negative indicator species of the NPMS were selected according to a process that was intended to satisfy multiple criteria relating to the minimisation of bias and ease of use by participating citizen scientists (Pescott *et al*. 2019). These species were shown by Pescott *et al*. (2019) to be capable of retrieving known ecological gradients present in other plant community datasets covering the UK, but were not specifically selected for their particular responses to known drivers of environmental change. The summary information collated here across 13 observational studies and reviews indicates that even this limited review of the literature suggests that our selected species will likely be appropriate for detecting various types of environmental change affecting plant communities. Although this is not a formal meta-analysis, and some of our extracted effect directions for some species may not be accurate reflections of the true underlying effect in any particular environment, the overall coverage across all drivers suggests that the selected indicator species are unlikely to be without value for learning about environmental change in UK plant communities. This is not unexpected given the conclusion of Pescott *et al*. (2019) regarding the representation of ecological gradients of these indicator species noted above.

2.5 Developing a national indicator for the NPMS

The intention is to develop a straightforward and easily interpretable national indicator for the NPMS. An overall and habitat-based indicator based on trends in count data (e.g. species richness or positive indicator richness) is discussed here.

2.5.1 Introduction

Indicators should be straightforward and easily interpretable, but also tailored to accurately index the particular aspect of an ecosystem, habitat, or community that they seek to represent. The collection, description and analysis of data for the production of an indicator must therefore have some specific end in sight. At the same time, any particular dataset, such as the NPMS, may support a variety of end product indicators, depending on how data are combined. Different approaches will suit different aims and will index different properties of a system (e.g. see section 2.3). Ultimately the NPMS was designed to track trends in abundance for plants associated with semi-natural habitats that are a priority for biodiversity conservation, linked to this is a desire to assess the "quality" of such habitats (Pescott *et al*. 2019). This section is not designed to scope out every possible indicator that could be formulated for NPMS data, but to present an initial proposal that could be implemented rapidly using existing methods. Here, then, we outline a proposal for a plant species richness indicator derived from plot data collected within the NPMS. The framework is flexible and could be extended to incorporate plot data collected under other schemes (e.g. the Countryside Survey; CS). The focus on this initial proposal is on richness in plots (i.e. counts of species or other taxa recorded). Plot-level species richness (local alpha diversity *sensu* McGill *et al*. 2014) in itself is of course a limited measure of biodiversity change, in that it does not take species' identities into account, potentially masking species turnover. However, we note there that the flexible proposal outlined here could be used for any type of count data, and that applying the approach to NPMS positive indicator species is likely to be a more appropriate approach to indicating quality using plot-level richness. Positive NPMS indicator species were chosen to be representative of typical stands of semi-natural vegetation, and so increases or decreases in these sets of species are likely to be more clearly linked to a conservationist's conception of quality than total species richness (e.g. see section 2.3). Other ways of summarising NPMS data to indicate other aspects of quality, e.g. national summaries of the frequency of particular ecological groups of species, are being developed elsewhere.

2.5.2 Proposal

NPMS volunteers record species within small plots (typically 5 x 5 m) across the British countryside. Once their plots are selected (an activity restricted to the first year of a volunteer's engagement with the scheme), the volunteer makes two decisions: which level of habitat discrimination to record at (broad or fine) and which level of expertise to record at (Wildflower, Indicator, and Inventory). The simplest approach to modelling these data, whilst also allowing for the focus on different subsets of species implied by these two decisions, is arguably to model some element of plot richness (e.g. species richness or positive indicator richness) in a count data framework, whilst adjusting for the different recording levels and habitat discrimination (as well as other factors such as habitat type). Such an approach allows for the incorporation of all data and allows for the estimation of the effects of covariates (such as surveyor level) as an integral part of the modelling process. We note that additional plot data could also be jointly analysed under such a scheme by including additional covariates to account for scheme type (e.g. NPMS versus CS), something attempted by Staley *et al*. (2019) in an attempt to develop a counterfactual for agri-environment scheme management. (See also the discussion in section 3.4 below).

Bayesian statistical modelling provides a way of running hierarchical models, allowing for missing data, and accounting for unbalanced and/or small samples (which is likely to be the case for some combinations of habitat and surveyor level). Integrated nested Laplace approximation (INLA), a deterministic algorithm used for Bayesian inference (Rue *et al.* 2009), uses approximations to produce marginal posterior distributions for all estimated parameters (Blangiardo & Cameletti 2015; Rue *et al*. 2009), and is used here due to its speed and flexibility.

The NPMS data modelled here were collated for all taxa recorded per plot for both 2015 and 2016. This summary outlines the key results from this activity, whilst the technical appendix in Annex 2 below provides the full set of exploratory models considered.

2.5.3 Models

A general model for these data, as implemented within INLA, can be specified as follows:

$$Species\ richness_{ij} = Poisson(\lambda_{ij})$$
$$\lambda_{ij} = \exp(beta0 + (beta1 \times year) + (beta2_{1\ldots K} \times level_k) + (beta3_{1\ldots L} \times habitat_l) + f(SPDE) + f\left(monad_j\right))$$

Where:
i = plot; j = monad; k = surveyor level; l = broad habitat;
beta0 is an intercept;
beta1 is the year effect;
beta2 is a vector of surveyor type effects;
beta3 is a vector of broad habitat effects;
f(SPDE) takes account of broad, between-monad, spatial autocorrelation (Blangiardo & Cameletti 2015);
f($monad_j$) takes account of the nesting of plots within monads (i.e. the monad is used as a random effect).

This formulation states that beta0 is the mean intercept across all plots and monads; ε_{ij} is the random Poisson error term for the record in plot i within monad j; λ is the parameter that defines this Poisson process; and SPDE is the stochastic partial differential equation, which is a computationally efficient approach to representing the underlying spatial 'process' (Blangiardo & Cameletti 2015). There are many variants of this model, such as treating surveyor type and broad habitat as random effects and excluding monad from the model. These are explored in more detail in Annex 2.

A habitat-specific model was also subsequently considered in order to demonstrate how habitat-specific trends could be produced. These models follow the specification given below, using data for a single broad habitat only:

$$Species\ richness_{ij} = Poisson(\lambda_{ij})$$
$$\lambda_{ij} = exp(beta0 + (beta1 \times year) + f(SPDE) + f(level_k))$$

Where:
i = plot; j = monad; k = surveyor level;
beta0 is the mean intercept across all plots/monads;
beta1 is the year effect;
f(SPDE) takes account of the spatial autocorrelation;
f($level_k$) takes account of the within surveyor level variability (i.e. here this is treated as a random effect).

2.5.4 Results

A series of models were run in INLA to assess the effects of year, survey type, and NPMS broad habitat, whilst taking account of the non-independence of data within monads and broader, landscape-scale spatial autocorrelation. The model results suggest that controlling for the nesting by monad, spatial autocorrelation and surveyor type is over-fitting the model: fitting a model with all three terms to the current two-year dataset results in some very uncertain parameter estimates. We therefore considered a simplified model with year as a fixed effect, controlling for spatial autocorrelation, and with surveyor type and broad habitat as random effects, but not incorporating monad as a random effect. This model showed little difference in the estimated species richness across the two years of NPMS data available (Figure 5). Figure 5 summarises the year effects estimated by this model; other summaries could also be extracted e.g. the effect of survey type on species richness.

Figure 6 gives the habitat-specific outputs (i.e. model estimates of species richness) for the following NPMS broad habitat types: “Broadleaved woodland, hedges and scrub”, “Lowland grassland”, “Arable margins” and “Heathland”.

2.5.5 Discussion

The current models assess species richness across all species, regardless of whether the plants are considered NPMS indicator species or not. As noted in the introduction, future model developments could deal with richness quantified using the positive indicator species only, as a better index of habitat quality; ratios of positive to negative species could also be considered, although these types of metrics can be difficult to interpret (e.g. does an increase indicate a change in the positive or negative species considered?), and may require other arbitrary decisions to avoid dividing by zero.

Additional covariates could also be incorporated in future developments; for example, the inclusion of survey month as a covariate might help to reduce variance around overall and habitat-specific trends, although if plot samples are typically well-spread around the two general periods recommended for survey in the NPMS guidance (i.e. late spring/early summer and mid/late summer), then it is unlikely that the inclusion of survey month in models would change the direction (or lack of direction) of a trend itself.

We also note here that the current models do not take account of temporal autocorrelation, which may be important in the following cases: (i) where one is seeking to evaluate the impact of a particular covariate in a space-for-time type analysis, and temporal trend is not of direct interest; (ii) where year (or other short time period) effects are of direct interest independently of longer-term time trends; and (iii) where explanation of a temporal trend is desired, and one is seeking to avoid confounding this with other temporally-structured covariates (which may or may not be known). Consideration of these issues will be more meaningful when we have more than two years of data. Note that it is ultimately possible to implement both forms of autocorrelation within INLA (indeed, one of the key benefits of using the INLA framework for Bayesian hierarchical modelling is its flexibility).

The development of this framework means that additional questions can now be addressed: for example:

- A comparison of NPMS indicator species metrics versus “all species” metrics could be conducted
- Uncertainty (e.g. in the form of 95% credible intervals) could be assessed within and between fine- and broad-scale NPMS habitat indicators
- Links to other types of metrics (e.g. see section 3.4 below) can be evaluated

Further work in this area could address alternative ways of using the species data collected by the NPMS; making fuller use of the proportional cover and occupancy data to produce species-level trend lines for example.

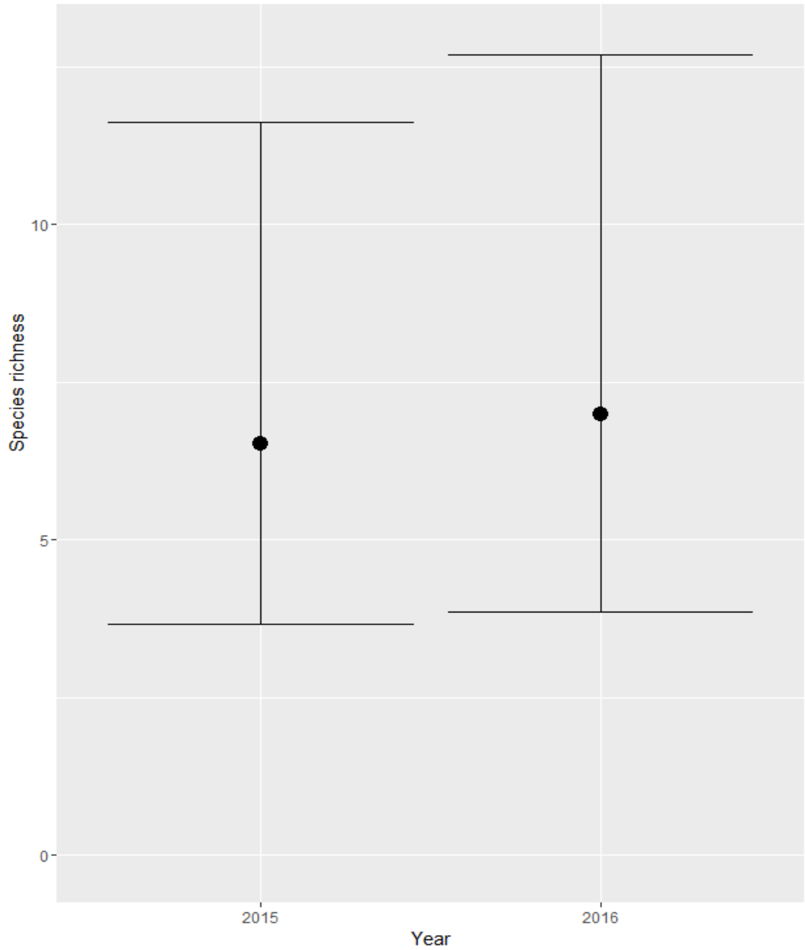

Figure 5. Estimated median species richness (with 95% credible intervals) in 2015 and 2016. Results from Model 3.8b (see full technical summary in Annex 2 for model numbering) i.e. year as fixed effect, taking account of between-monad spatial autocorrelation and the dependence between surveyor type levels and between broad habitat levels.

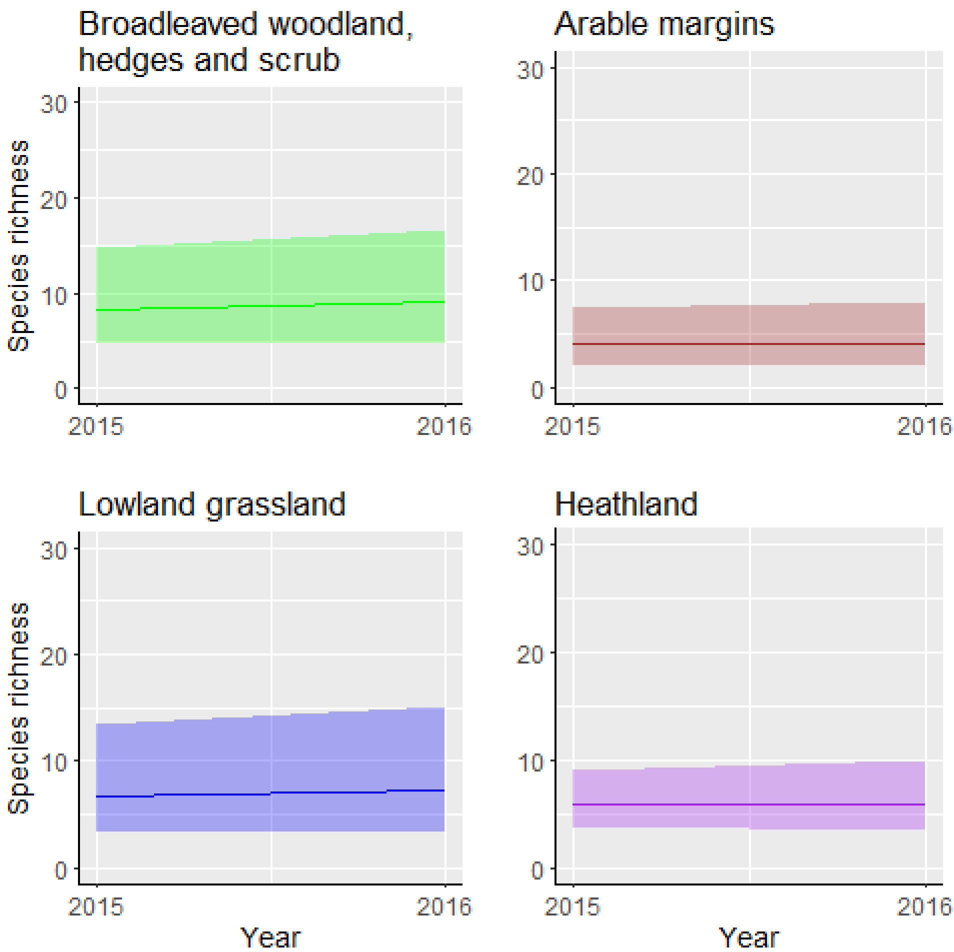

Figure 6. Estimated median species richness (with 95% credible intervals) in 2015 and 2016, across the UK, for specific NPMS broad habitats.
See the methods section above for more detail on the model used.

3 Further Use of the NPMS

3.1 Links to other UK biodiversity monitoring schemes

Finding a practical means of linking the NPMS to other monitoring schemes through survey of overlapping areas has distinct advantages:

- tighter linkage of drivers and responses across taxon groups;
- increased power for detecting and interpreting environmental change;
- investigation of interactions between taxa.

Currently, some linkages have been established with the Pollinator Monitoring Scheme (which surveys pollinators in a selection of NPMS survey squares), and the potential of links between different plant monitoring schemes is being investigated. It is recognised that linkages with some taxa are not feasible or practicable because of differing needs of the schemes.

Limited availability of volunteers to carry out the surveys can be a limiting factor in many parts of the UK. While many surveyors are happy to record a few extra attributes compatible with their primary interest, it is recognised that asking them to carry out a completely different survey, or additional onerous tasks, may not always be feasible.

With any plans of this kind going forward, surveyor impact (e.g. trampling pressure) on the survey plots must be taken into account and minimised.

The creation of a network of 1 x 1 km squares (monads) throughout the United Kingdom (including the Channel Islands and the Isle of Man) enables us to consider the potential for links with other volunteer-based and professional monitoring, with the aim of increasing scheme efficiency and power to inform about habitat change. Links can be considered both from the point of view of the methodology used by the NPMS in selecting the set of potential locations for monitoring (Pescott *et al*. 2014a), and from the point of view of the subset of 1 km squares that have actually been allocated and surveyed under the first years of the scheme. One other interpretation of ‘linked’ monitoring involves complementarity between schemes; this is discussed in the final part of this section (3.1.4).

The process through which the first ‘tranche’ of NPMS squares was selected created sets of weights intended to bias the selection process towards monads with larger areas of nationally rarer land cover types (as defined by the CEH Land Cover Map 2007; Morton *et al.* 2011). This was followed by a geographical stratification (by 100 x 100 km square of the British Ordnance Survey grid) designed to increase the evenness of square availability across the British Isles. These processes mean that data collected from surveyed squares could potentially be weighted during analyses in order to adjust for these introduced biases, producing metrics that would, in theory, be more representative of the whole of the landscape of the British Isles.

We emphasise here that whilst the use of these weightings is technically possible, and would alter the outcomes of analyses according to the weights used, the ‘truth’ of such weighted results is essentially unknowable, except in reference to another contemporaneous unbiased survey of the population that the weighting was intended to produce a match to (in much the same way as the actual bias present in a survey is empirically unquantifiable without an unbiased survey of the same population for comparison). Thus, the use of weightings that are intended to remove the inbuilt biases towards areas richer in rare habitats, or any subsequent bias towards the preferential survey of monads closer to conurbations, implies that the researcher is happy with the weights used as a close index of the process that is being factored out.

Links to other types of monitoring could therefore be based around the entire NPMS sampling network as originally conceived (e.g. the entire set of tranche 1 squares), or to the squares that have received surveyor visits up to a particular date. As noted, the use of square weightings could potentially increase the comparability of some analyses. For example, a hypothetical, professional-led survey that sampled all NPMS squares could potentially be made more comparable with the subset of existing volunteer surveyed NPMS squares by weighting the NPMS volunteers-surveyed locations to take into account the geographic bias involved in a square being surveyed. (That is, the use of weights here would be intended to down-weight areas that were preferentially likely to be surveyed by virtue of their being close to, for example, large conurbations, and up-weight those locations that were less likely to have been surveyed based on their location).

The following discussions assume that the co-location of external monitoring with NPMS squares is either total (i.e. monitoring has occurred at the same set of locations); the situation where an external survey uses a different subset of squares from the NPMS tranche 1 set to those that have actually been subject to volunteer survey is not further discussed, given that it is an unlikely scenario.

3.1.1 Spatial overlaps between monitored 1 km square locations

Many existing monitoring schemes (both professional and volunteer-based) have their own existing protocols for selecting and releasing (typically 1 km) squares. Therefore, there may be limited opportunities for additional co-location between existing schemes going forward, except for in those cases where there is occasional existing, co-incidental, overlap. There are more opportunities for new schemes to overlap with NPMS squares, and, indeed, this strategy was investigated within the National Pollinators and Pollination Monitoring Framework, which has led to the Pollinator Monitoring Scheme (PoMS) launched in 2017. In this case, in England and Scotland, squares for monitoring were selected from those NPMS squares that had been visited in 2015 or 2016 (Carvell *et al*. 2016).

The JNCC Terrestrial Evidence 'Partnership of Partnerships' ('TEPoP'; the agreement through which volunteer-based biodiversity monitoring schemes are now sharing ideas and results) and the linked programme of Terrestrial Surveillance and Development Analysis, led by CEH and the British Trust for Ornithology, are likely to provide further opportunities to develop such links.

Actual overlaps between monitored squares may be useful for the following reasons:

- Drivers and responses across taxon groups can be more tightly linked (i.e. cross-taxon analyses are facilitated), without the need for assumptions about processes acting similarly across separate sets of squares. Cross-taxon analyses may be particularly important for analyses of processes or stocks that researchers wish to quantify within a 'natural capital' framework (Kareiva *et al*. 2011)
- Where environmental drivers are acting in concert on separate groups of taxa (e.g. farmland birds and arable plants), considering trends or other evidence together may increase the power to interpret environmental change. Co-located data should help to reduce the uncertainty associated with conclusions arrived at through the comparison of different study locations, where the possibility of confounding variation is more likely
- Interactions (both biological and statistical) between taxa can be directly investigated
- Land access permissions could potentially be shared and simplified (although we note the need to have regard to the new EU General Data Protection Regulation in this area)

- Independent information sources on the same environmental feature (e.g. habitat extent or type information collected by two separate surveys, or from one ground survey and Earth Observation (EO) data)

Clearly, it is not only ongoing monitoring that could share locations with the NPMS. One-off sampling campaigns could also utilise the network, for example, for eDNA, soil biodiversity, or direct measures of abiotic variables (e.g. nitrogen deposition or carbon fluxes).

3.1.2 The use of actual plots for other sampling (e.g. eDNA, soil biodiversity, pollinators *etc.*)

As for square-based co-location, the actual plots could also be used. (Recall that NPMS habitat plots NPMS are normally 5 x 5 m, except in woodlands (10 x 10 m) or linear features (1 x 25 m). As noted above, for processes acting at fine-scales (e.g. for soil biodiversity drivers or the interactions between plants and abiotic variables), the collection of co-located data at this scale is likely to increase the ability to infer causative processes considerably.

3.1.3 Asking volunteers to do additional tasks

The co-location of other monitoring could potentially be in the form of NPMS volunteers conducting this other monitoring themselves. For example, the new PoMS scheme has, in England and Scotland, approached NPMS volunteers (through the NPMS coordinator) regarding the possibility of these volunteers carrying out simple pollinator monitoring procedures in their squares. Clearly there are trade-offs with respect to this possibility, the NPMS does not want to overload its volunteers. A key advantage here, however, is that the volunteers will often have already organised access to the land and, requesting that they perform additional tasks, is efficient and straightforward in that it does not require any transfer of personal data. An alternative is that volunteers from other schemes are encouraged to carry out their scheme's protocols within NPMS squares: for example, the establishment of UK Butterfly Monitoring Scheme transects would be particularly straightforward given the fact that there is a certain amount of free choice in where such transects are established within a square.

It is of course expected that any such additional surveying would be carefully discussed amongst the NPMS Project and Steering Groups before proceeding, and would have to be considered enjoyable, interesting, and achievable before being endorsed as a volunteer-based task by the NPMS. We note that some additions might be very simple items that would enhance the NPMS protocol at very little cost to the surveyor; for example, asking volunteers to note whether a plant is in flower may provide information on phenology, habitat management, pollinator resources, and the surveyor's ID skills, for almost no extra effort. Other possibilities that have been mentioned range from more specific questions on tree health, to the collection or validation of some forms of habitat mapping data. It is our general expectation that asking volunteers for small items of additional botanical detail is likely to be more successful than asking for the adoption of larger projects focusing on other taxon groups, although some other schemes have had success in this area (e.g. the Breeding Bird Survey has added mammal and butterfly recording as an option, and around 90% of bird recorders now look for mammals; N. Newton, JNCC, pers. comm.)

3.1.4 Scheme complementarity

As well as the co-location of squares and plots, scheme complementarity should also be considered. 'Professional' monitoring of various sorts could be used to compensate for spatial biases of recording within the NPMS, or for the collection of more technical data types. It has been suggested within CEH that a re-survey of Countryside Survey (CS) "X"-

plots (Maskell *et al*. 2008) could provide a counter-factual to the NPMS as a systematic-random sample of the countryside, particularly for widespread habitat types.

One possible future for the NPMS then, is in the context of complementing other national vegetation monitoring, including paid surveys. The NPMS itself would likely benefit from things delivered by other professional or volunteer-led schemes (see section 3.2). Any professional “top-up” to the NPMS, for example improving the coverage of some priority habitats or remote areas, should consider the pros and cons of adding this to an existing scheme such as the CS or by focusing on the relevant un-surveyed NPMS squares.

3.1.5 Conclusions

The topic of links to other types of monitoring is evidently a large topic, and one that will clearly have to be influenced by the activities and needs or other organisations; unforeseen opportunities will no doubt also present themselves and require decisions. The links to the PoMS have already shown how this can work, with the NPMS coordinator liaising with volunteers to both keep them informed about non-NPMS activities in their squares, and to offer (but not require) other surveying opportunities.

Links to other monitoring is also likely to emerge around the topic of the use of NPMS methods, and this is something that has been extensively discussed at the 2016/17 stakeholder meetings in England, Scotland and Wales. The possibility of promoting the NPMS methods for wider monitoring is likely to be something that is addressed in the next phase of the project; the provision of toolkits for external organisations is also something that was suggested at the Scottish stakeholder meeting. Such initiatives should also enable conceptual links to be made between local and national monitoring, in that there are likely to be clear opportunities for comparisons to be made between local and national datasets.

Finally, proponents of co-location should clearly be alive to the possibility of surveyor impacts upon surveyed locations. Too frequent visits to sensitive habitats may result in changes to species’ populations, creating changes that are representative of, for example, human trampling pressure, rather than the broader changes in the countryside that the scheme is intended to monitor.

Note that the similar topic of links to opportunistic or semi-structured monitoring of the type conducted by the BSBI is dealt with in section 3.2 of this review.

3.2 The NPMS as a framework for ‘opportunistic’ biological recording

This section discusses how the NPMS could be extended to make use of ‘opportunistic’, or semi-structured, plant surveys and records.

The BSBI is considering moving towards more structured types of monitoring after the current atlas work is completed, and the potential for aligning the two schemes is discussed.

Opportunistic recording has the advantage of creating large volumes of data, including from areas where regular recording may currently not be taking place. This can be utilised in a range of ways when combined with the systematic NPMS data collection.

Disadvantages of opportunistic data collection include the lack of consistency in survey locations, survey time and timing, and hence have low repeatability. If these can be reconciled, which with modern analytical methods is possible, opportunistic recording could provide a powerful addition to the NPMS. Examples of such benefits already exist for other taxa such as butterflies (see section 3.3).

3.2.1 Background

Over the last 60 years botanical recording in Britain has primarily focussed on mapping the occurrence of species within OS grid cells (Pescott *et al*. 2015), with the results published as 10 × 10 km (hectad) distribution maps in two national atlases (Perring & Walters 1962; Preston *et al*. 2002) and numerous local and county floras. Today mapping occurrences within 1 × 1 km grid squares (monads) is the norm, with much higher resolutions captured for more ‘interesting’ species (such as local or national rarities, or unusual aliens) using hand-held GPS units and, increasingly, through the use of recording apps on smartphones (e.g. the iRecord app). This traditional ‘atlas-style’, or ‘opportunistic’, recording is largely unstructured with respect to the squares that recorders visit, the places they record within squares and the time they spend recording (Rich 1998; Rich & Smith 1996). This means that recording effort has varied significantly both spatially and temporally, leading to difficulties in the analysis and interpretation of changes over time (Rich & Woodruff 1996; Telfer *et al*. 2002), although a range of statistical approaches can now be used to reduce the significance of these potential biases (Isaac *et al*. 2014). In addition, traditional ‘atlas-style’ recording has largely ignored questions of abundance and habitat occupancy, at least in a systematic sense.

In comparison, the NPMS utilises a structured sampling design and field methodology that focusses on the abundance of species within small plots located in habitat patches, rather than simply presence within grid-squares. In addition, the NPMS focusses on a subset of species rather than all species present (Wildflower and Indicator Level), although volunteers are also free to record all species if they wish (Inventory Level). The nearest equivalent BSBI surveys are the Monitoring Scheme/Local Change surveys, which included more standardised recording of species within a national sample of tetrads (Braithwaite *et al*. 2006; Rich & Woodruff 1996) and the Threatened Plants Project which required volunteers to revisit a random sample of known populations of 50 threatened species to collect information on abundance, habitats, management and threats (Walker *et al*. 2017). Crucially both surveys were based on sets of unbiased sample locations (with respect to the populations about which they were designed to provide information for) and utilised standardised methodologies.

In this section we explore how NPMS could provide a focus for more general 'atlas-style' recording, the benefits that this would have for NPMS and plant monitoring more broadly and how the two might be integrated.

3.2.2 NPMS as a focus for opportunistic recording

The BSBI is currently working on a third atlas of the British and Irish flora, recording for which will cease at the end of 2019. Discussion is ongoing as to the nature of post-atlas recording, but the BSBI is likely to move away from the 'atlas-style' approach towards the monitoring of a sample of monads across a range of landscape types using a standardised method, allowing for more direct comparisons between the numbers of species present, their abundance, habitat associations, change over time, etc. Although the BSBI already has a sample of c. 650 well-recorded tetrads that could provide a focus for such a scheme (Local Change; Braithwaite *et al*. 2006), the NPMS framework provides a potentially more suitable alternative because they are already being monitored regularly (in most cases on an annual basis, whilst Local Change tetrads have been recorded only twice, 16 years apart) and, as a consequence, we have a good knowledge of their constituent habitats and environmental conditions, as well as information on access and land ownership. The NPMS framework has already provided good geographic coverage across the UK, although upland regions remain rather poorly represented (e.g. see Figure 1 above), a feature shared with other volunteer-based structured biodiversity monitoring. Linking BSBI recording to NPMS, as discussed in section 3.2.3, would also be efficient in terms of data management, analyses and volunteer support and, more importantly, would add significant value to both NPMS and BSBI monitoring more generally by allowing direct comparisons between trends for NPMS plots and the countryside surrounding them.

From a wider plant monitoring perspective, some of the main benefits of combining NPMS sampling with opportunistic recording could be:

- The ability to monitor a much larger pool of species than currently recorded within the NPMS, which taken collectively would improve overall trend assessments for species and habitats
- Helping to define local species-pools for NPMS habitats, therefore helping with the interpretation of trends
- Quantifying the detection rate of species at different scales in relation to their abundance, life-history, habitat, visual apparency, *etc*. Note that as well as providing information that can be used to assess the likely accuracy of conclusions about species' increases or decreases, improved estimates of detectability under more standardised conditions could also improve Bayesian occupancy modelling of 'opportunistic data' (Isaac *et al*. 2014). Currently such models attempt to estimate detectability by comparing the number of detections to the number of visits during a time period. This method, however, is highly dependent on a large number of variables, not least of which is the number of visits available during a period. Fixed, empirical estimates of species' detectability at different scales could be a more consistent way of accounting for detectability in such models
- Provide a sample of 'well-recorded' squares which could be used to model/interpolate species distributions in areas where the recording intensity is poor or unknown
- Increase participation in NPMS amongst more expert recorders involved in opportunistic recording, with the potential to improve coverage in under-recorded areas

3.2.3 How could opportunistic recording be integrated with the NPMS?

Unstructured recording

Traditional ‘atlas-style’ recording would be the simplest approach to recording NPMS squares, whereby recorders spend as much or as little time recording where they like in the square, generating a list of species seen. List-length would therefore be heavily influenced by where, when and for how long recording took place, as well as by recorder expertise. This approach would only require minimal support and guidance but would be poor in terms of repeatability, therefore reducing the validity of the results. Indeed, the number of species that have been recorded during this type of normal BSBI recording activity within the 608 monads which are also monitored as part of NPMS shows large variation (Figure 7), largely due to variations in recorder effort (intensity).

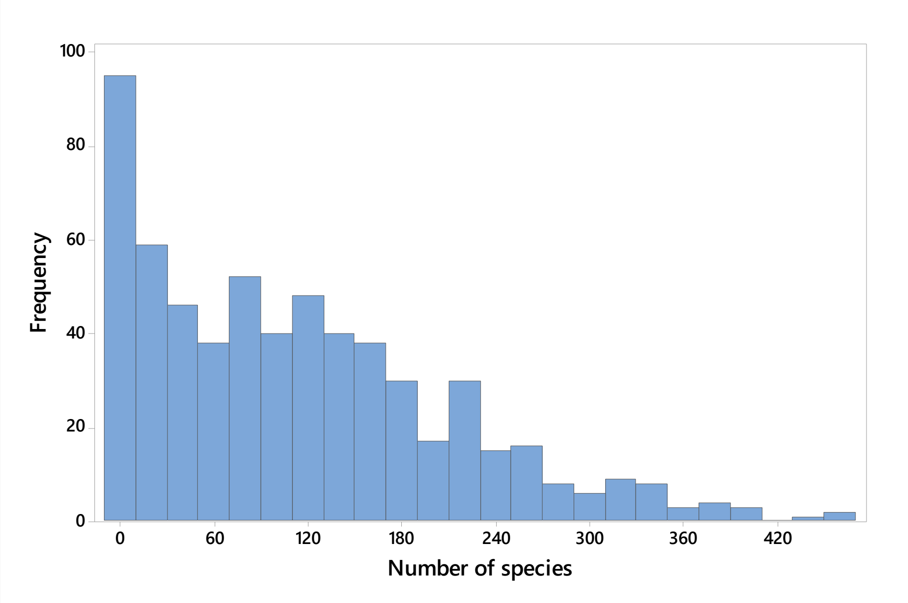

Figure 7. The number (frequency) of 1 km squares in each species richness bin, where species richness is the number of species recorded ‘opportunistically’ by BSBI recorders, across all BSBI data. The 1 km squares included are those monitored by the NPMS since 2015 (n = 608). Note that the lowest bin starts at 1 (i.e. all squares have >0 species recorded).

Semi-structured recording

This approach allows for opportunistic recording but is more structured in terms of where volunteers record and for how long. This was the approach taken in the BRC/BSBI Monitoring Scheme/Local Change where recorders were asked to spend no more than 10 hours recording in a typical lowland tetrad during three or four visits at different times of the year (although few recorders complied with this request). Recorders were asked to visit a ‘range of representative habitats’ and areas likely to support notable species, playing close attention to where botanists had recorded on the first visit. Some habitats and species were avoided (e.g. difficult species, planted shrubs and trees in private or public gardens). This approach made the results more comparable than would have been the case if an ‘atlas-style’ approach was taken, although variations in re-find rates were still likely to have been significantly influenced by where recorders went and by how long they spent looking.

Structured recording

To ensure greater repeatability a more structured method is required. This would specify where and when recording should take place and for how long. Such an approach would need a degree of standardisation in terms of:

- **the amount of time spent recording** taking into account the number of recorders, the accessibility of the square and the time spent recording on previous visits. We would envisage a ‘sliding scale’ with more time needed to record a diverse lowland square than an upland square dominated by a few habitats
- **when the squares are recorded** with visits in different seasons to minimise overlooking taking into account remoteness/altitude/accessibility of the square (i.e. fewer needed in more remote locations) as well as the phenology of the major habitats (i.e. need for early visits to woodlands and late visits to saltmarsh/coastal habitats)
- **the areas visited in each square**. This is the most difficult aspect to control because the areas surveyed are often highly influenced by access permissions and topography. Having said that, a structured approach might require a recorder to record along a route of between 1-2 km between a range of representative habitats in the square, regardless of how rich or poor, but most importantly that the areas visited/routes taken were captured and re-visited on subsequent visits. This would not preclude new areas being visited on subsequent visits, but these would need to be noted so that any new species found can be differentiated as ‘previously overlooked’
- **appearance/disappearance** would be critically assessed during revisits and any changes would be attributed to a standard list of terms (e.g. arable converted to pasture, previously overlooked, *etc*.) and would take into account whether a species was likely to have been overlooked
- **revisits would be needed within a minimum timeframe** (depending on their accessibility) so that there is a sufficient number surveyed annually to reveal trends for species and habitats. The minimum timeframe would vary depending on the nature and remoteness of the habitats (e.g. decadal for montane, <5 years for lowland agriculture)
- **recorder expertise** would need to be scored so that this can be taken into account during assessments of appearance/disappearance and analyses

Additional information that might be gathered during more structured recording such as this might include:

- habitat associations using the NPMS habitat scheme
- abundance values within a square, either using a qualitative score such as DAFOR or a semi-quantitative score such as the number of hectares occupied of those surveyed (e.g. Domin scores, <4, 5-10%, 11-25, 26-33, *etc*.)

Figure 8 places this type of activity alongside the other types of monitoring discussed in this document. The ‘Plant Portal’ is a quadrat data aggregation website that is under development at CEH; this would allow for the archiving of historical, and the collection of new plot data. New plot data could be collected according to existing protocols such as that of the NPMS, although the types of plot data that the Portal will accept will not be limited.

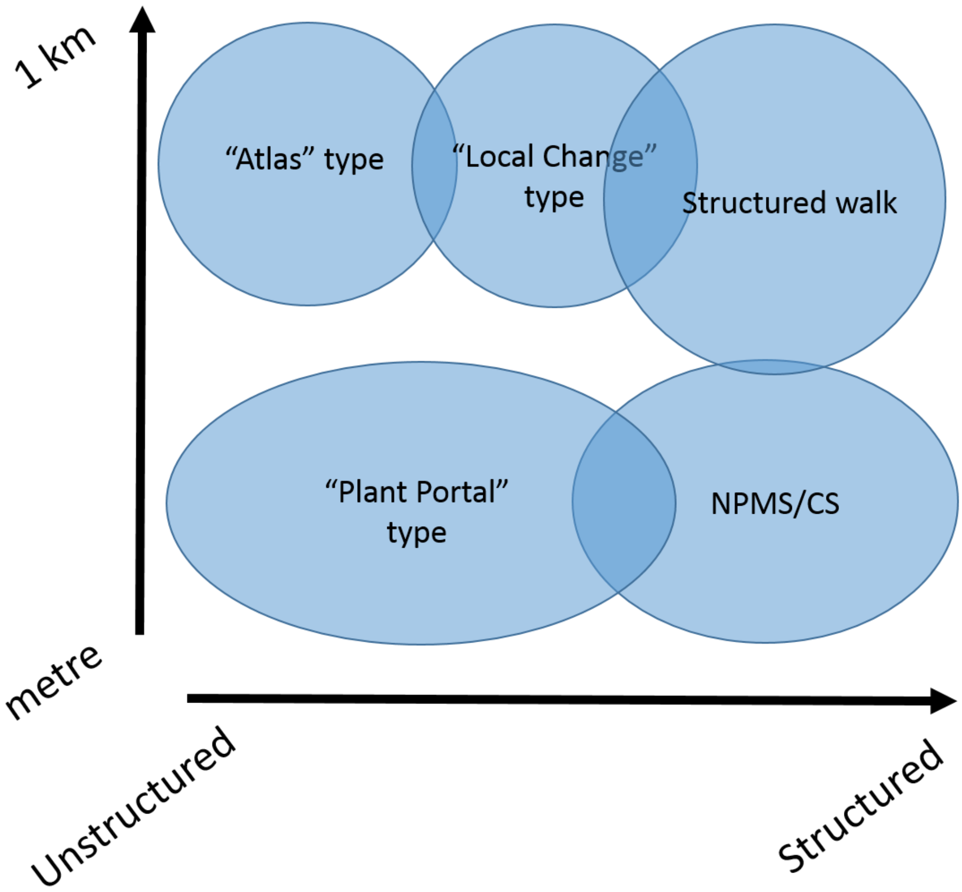

Figure 8. The different types of monitoring as discussed in this document.
A more structured approach to general botanical recording could complement the NPMS in various ways. CS = Countryside Survey.

3.3 Linking data types using Bayesian hierarchical models

This section considers one of the potential directions that NPMS could take as the scheme is developed in its next phase.

Data integration from different schemes and scales is investigated, and it is possible that Bayesian statistical modelling can be used to integrate different plant monitoring datasets as different expressions of the same underlying state, and hence potentially produce results that are greater than the sum of the component parts.

One of the outputs could be predicted abundance maps that could be used to e.g. define variations in natural capital or identify areas of high levels of ecosystem services. They could aid in better targeting of conservation interests, and to direct further survey work.

3.3.1 Data integration: the background

Mapping species distributions at large spatial scales (i.e. large spatial grain size) has been a mainstay of biogeography since the middle of the 20th century (Preston 2013), and has provided the data behind many macroecological investigations and conservation assessments (Powney & Isaac 2015; van Maes *et al*. 2015). The 'opportunistic' data underlying such projects exist in great abundance for Great Britain, often being collected by expert amateurs in a volunteer capacity (Pescott *et al*. 2015; Preston *et al*. 2002); these data may often be more accurately described as 'semi-structured', given that they are frequently the result of extensive searches of a grid cell following a methodology aimed at the production of a distribution atlas for a particular taxon group (Balmer *et al*. 2013; e.g. Walker *et al*. 2010b). Increasingly, more is being demanded of such 'citizen science' data, with reporting for national (Defra 2016) and international trends (Dirzo *et al*. 2014), as well as ecosystem service assessments (Oliver *et al.* 2015), resting on their analysis (Dornelas *et al*. 2013).

At the same time, occasional, but more structured monitoring of species' abundances at fine scales also occurs. Such surveys may be conducted under the auspices of national biodiversity and habitat surveillance programmes staffed by professionals, such as the UK Countryside Survey (Carey *et al*. 2008) or the Swiss Biodiversity Monitoring programme (FOEN 2014), but such monitoring may also be volunteer-based (Pescott *et al*. 2015; e.g. Roy *et al.* 2015), as with the NPMS. A natural question to ask in this situation is whether extensive sets of volunteer-collected occurrence data at large scales can provide information about fine scale local abundance data collected from, for example, NPMS plots, in order to increase the geographic area for which predictions of abundance can be made (Pagel *et al.* 2014). Indeed, the integration of different types of monitoring data in this way may be cost effective, and represents a key challenge for long-term monitoring (Gimenez *et al*. 2014; Lindenmayer 2012). Recent work on combining large scale butterfly distribution data with fine scale transect abundance data from the volunteer-based UKBMS has demonstrated that the integration of such data sources may be possible where the observation processes leading to the separate datasets can be linked to an underlying 'true' state or states to be estimated (Pagel *et al*. 2014). In such a way the uses of data collected at small scales by NPMS volunteers could be enhanced.

Pagel and co-authors (2014) focused on the potential for combined abundance/occurrence data to provide evidence for spatial variance in trends across species ranges, pointing out that datasets "that cover large geographic areas rarely include population abundance data at high temporal resolution" (see also Beck *et al*. 2012). In this way temporal trends for all grid cells could be estimated, even in the absence of fine scale monitoring of abundance. For plants in the UK, structured monitoring of plant abundance at small scales has not historically been conducted on an annual basis; however, the existence of periodic structured monitoring of plant abundance in the form of the UK Countryside Survey (Carey *et al*. 2008) does allow for a potential relationship between small scale plant abundance and larger scale observation processes to be explored. Linking together small scale abundances with larger scale occurrences may also enable the production of species distribution models that can be directly interpreted as abundance estimates, rather than as grid cell occurrence probabilities which are assumed to be related to abundance, "at least heuristically … in some kind of average sense" (Royle & Dorazio 2008: 127). In addition, the larger spatial extent covered by the opportunistic records may also allow for information contained within finer scale measures of abundance to be extrapolated to un-surveyed locations (Pagel *et al*. 2014).

There are other possible meanings of "data integration" besides the joint modelling of datasets that is discussed here. One area of research that is often encountered in the ecological indicator literature is that of the production of aggregated indicators, where trends from multiple populations, species, habitats, or combinations of these, are combined to produce a single indicator line (e.g. van Strien *et al*. 2016); however, this topic is not covered further here.

3.3.2 A botanical example of an integrated Bayesian model

Unpublished work performed at CEH in collaboration with the University of Hohenheim (Dr Joern Pagel) has resulted in the creation of a hierarchical Bayesian model that posits a link between "Atlas"-style distribution data and plot-level estimates of abundance. (Note that "hierarchical" in this context refers to a model fitted to data that are nested in some way, but also that the statistical model itself includes parameters that are estimated based on specified groupings; Gelman & Hill 2007.) This model focuses on both the large scale occurrence records and fine scale abundance data arising from an underlying area-based 'true' plant abundance; that is, we formulate a model of plant cover which links two separate observation processes occurring at different scales (Figure 9). To date, the two datasets explored are the percentage cover estimates of professional surveyors working at a small scale (200 m^2) within the UK Countryside Survey (CS), and detection/non-detection occurrence data collected by recorders of the BSBI, summarised for 100 km^2 (10 × 10 km) grid cells. Note, however, that the model could be applied at any scale, and that NPMS data could be substituted for data from the CS.

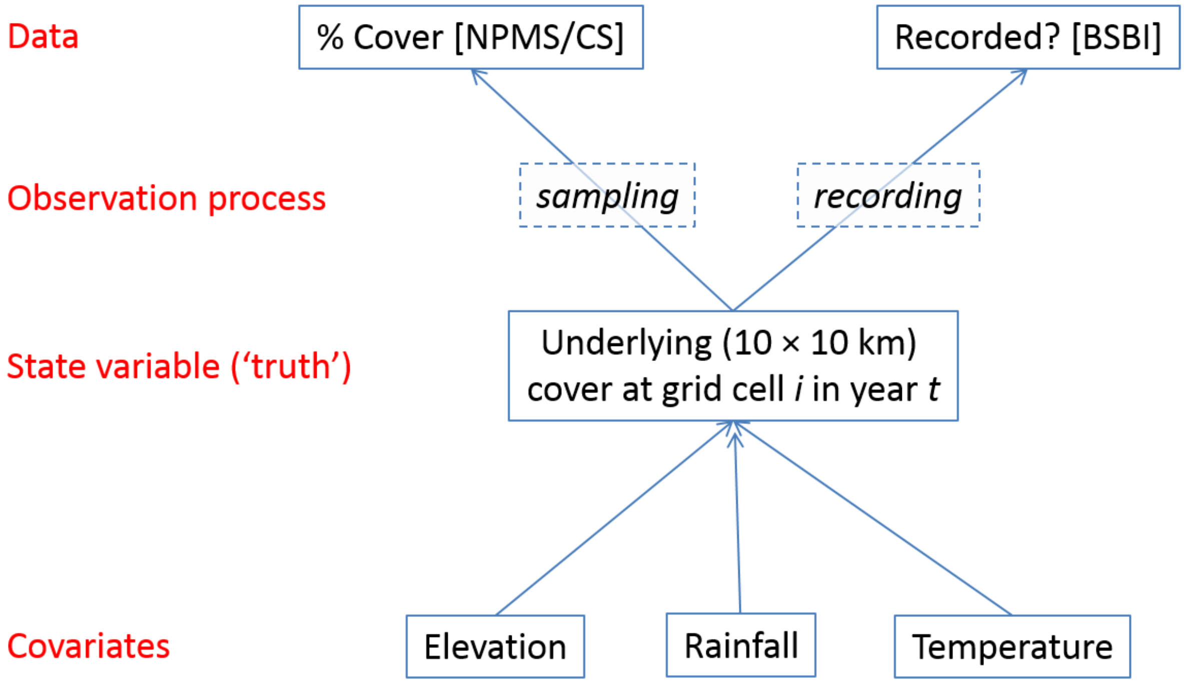

Figure 9. The conceptual underpinning of a hierarchical Bayesian model for integrating small scale abundance data, such as is collected by the NPMS, with large scale distribution data (i.e. 'atlas-style' data) for plants.

The model has been described mathematically (O.L. Pescott, S. Freeman & J. Pagel, unpublished manuscript), but we do not reproduce this here due to both the summary nature of this section and the relative complexity of the model. An additional reason is that the full model that we have described may ultimately be *too* complex for modelling the datasets for which it has been developed. This is not an uncommon finding in the ecological and evolutionary sciences, where datasets may be too small to contain sufficient information about the underlying processes posited to be important in creating the resulting data (Auger-Méthé *et al.* 2016; Erickson *et al.* 2017). As Auger-Méthé and colleagues (2016) state "[a]s a general rule decreasing the number of parameters to estimate [i.e. reducing complexity] and increasing the amount of data will help reduce [parameter] estimability problems". In relation to this, ongoing work on this framework has focused on model simplification, with an aim to discover whether simplified descriptions of the relationships between the two data types result in models with parameters that can be estimated. We note, however, that the model has been used to successfully recover parameters from simulated datasets (J. Pagel and O.L. Pescott, unpublished results).

3.3.3 Current results and future possibilities

Presented below are some of the early results from the Bayesian model described above (Figure 10).

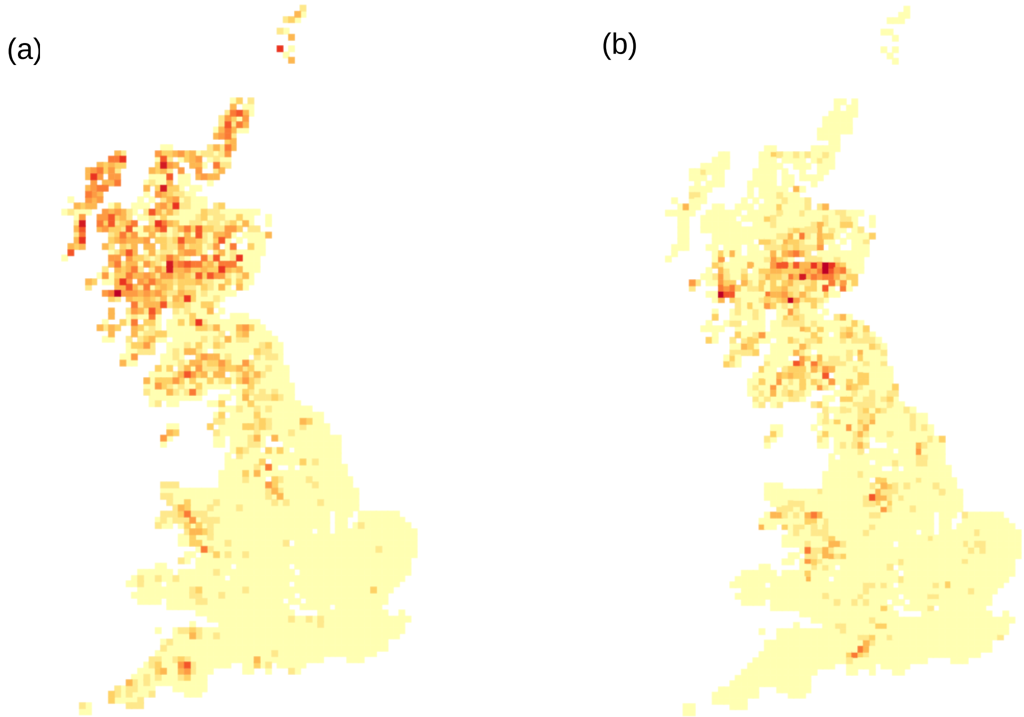

Figure 10. Maps of the predicted abundance (percentage cover at 10 × 10 km) for (a) *Calluna vulgaris* and (b) *Campanula rotundifolia* as estimated by our most complex hierarchical Bayesian model.

Note that these model runs did not include covariates (cf. Figure 9), and that these results are tentative, given that some of the parameters in these models were not well estimated (i.e. there was very high uncertainty that the model was able to make sensible estimates for some parameters using the available data). Darker colours relate to higher predicted percentage cover.

Ultimately, the aim is also to produce associated maps of uncertainty for these estimates (e.g. see Pagel *et al*. 2014), and to assess the added benefit of information gain over modelling the plot and distribution data separately. In this model, parameters are estimated using Markov Chain Monte Carlo (MCMC), allowing for very flexible model specification. However, MCMC methods can be very slow for complex models; the most complex model has been run for up to 4 weeks (note that this is for a single species), without achieving satisfactory convergence in all parameters. For this reason, alternative methods are also being investigated. Some of these involve making mathematical approximations in order to assess the posterior distributions of parameters (i.e. the estimated values that a parameter is likely, and unlikely, to take); one of these methods, Integrated Nested Laplace Approximation (INLA), is now well developed, and models run in this mode can take minutes or hours, rather than the days or weeks often required for MCMC methods. The speed, however, comes at a loss of flexibility, and, for this reason, colleagues at CEH Lancaster (Pete Henrys and Susan Jarvis) have reformulated our model for running in INLA. The early results are very promising, and it is expected that the two approaches to integrated botanical data modelling will be published separately, but also subjected to comparisons. This work, and further development of the MCMC-based model, form part of an ongoing NERC National Capability project in progress at CEH (2017-2020).

The fundamental aim of this work has been to exploit complementary information from different datasets, each with its own strengths and weaknesses, and a successful outcome (that is, extensive models of abundance for a range of British species) could have a number of potential applications. For example, there is increasing interest in the spatial distribution and variation in ‘natural capital’, where natural capital has been defined as “the assets or stock that yields a flow of valuable goods and services into the future” (Costanza & Daly 1992). The concept can be used in a variety of ways, and the definition of natural capital for any particular purpose may be subject to debate and research (Kareiva *et al*. 2011).

Accurate predicted abundance maps of species may be used to define areas of broad habitat (e.g. by coincidence mapping those areas predicted to be of high abundance for sets of habitat indicators) or of ecosystem service provision (e.g. by mapping those species that are considered to contribute to an ecosystem service; Oliver *et al.* 2015). Regardless of which outputs are thought to be valuable and useful to researchers and society, the production of maps of abundance, rather than large-scale distribution, is likely to link more accurately to a number of goods and ecosystem services (e.g. nectar provision; Baude *et al.* 2016).

Finally, the model discussed here has primarily focused on integrating datasets of different types that provide complementary insights into a single underlying state variable (see Figure 9). Further integration could be achieved by using multiple small-scale datasets in that part of the model. For example, where funds are limited, professional survey teams (e.g. a future Countryside Survey or equivalent) could be directed to areas where representation from volunteer-based surveys, such as the NPMS, is sparse. This would allow for more cost-effective coverage of the UK countryside, whilst also developing botanical skills and well-being of the surveyors involved (Walker *et al.* 2015). In such circumstances, large-scale distribution data might be primarily useful for providing historical baselines, although it is also possible that the continued integration of large-scale distribution data could remain important for the model’s predictive power. Future work could investigate developing rules of thumb for such integrative work, for example, testing scenarios in which different amounts of systematic and unstructured data are combined.

3.4 NPMS as counter-factual

National datasets such as NPMS have the potential to be used as a 'counterfactual' or 'control' when measuring the effectiveness of an intervention such as habitat management, or the impact of any other type of human activity or environmental driver.

Such investigation can be either carried out within NPMS by comparing monitoring plots with different management histories, or to use NPMS data as the baseline against which the change caused by an action is measured against by the subsequent monitoring. Both approaches have their inherent strengths and weaknesses.

If the NPMS data are to be used as a counterfactual with a different dataset, several considerations (discussed here) need to be taken into account to determine the suitability and compatibility of the NPMS data for a specific application. Of particular consideration are:

- Datasets need to be as close in time as possible to minimise the chance that other factors are causing the differences
- Representativeness of the landscape and habitat in the second dataset
- Equivalence of baseline plant communities – i.e. compare like with like
- Comparable sampling methodology and plot size
- Since the NPMS dataset contains three levels of survey detail (number of plant species targeted) appropriate subsets of data may need to be extracted to be comparable with the other dataset.

As the NPMS was designed to produce an overview of habitat status and trends, and to provide national level indicators, data uses such as the counterfactual are added benefits.

3.4.1 The use of 'counterfactuals' for estimating environmental change

An important topic in conservation biology and ecology is the quantification of the effectiveness of management interventions and their value for money (Ferraro & Pattanayak 2006). A particular focus in north-west Europe has been the desire to quantify the effectiveness of agri-environmental scheme (AES) interventions (Kleijn & Sutherland 2003; Sutherland *et al*. 2006), although ecologists have also considered the question of the effectiveness of protected areas, the designation of which typically implies the existence of at least some management differences compared to surrounding, unprotected areas (Gaston *et al*. 2006).

According to Ferraro (2009) these types of "[i]mpact evaluations assess the degree to which changes in outcomes can be attributed to an intervention rather than to other factors. Such attribution requires knowing what outcomes would have looked like in the absence of the intervention." That is, they require a 'counterfactual' or control.[1]

[1] Logically, 'counterfactual' and 'control' could be considered to be synonymous. However, given that the word 'counterfactual' has been used in the environmental literature as a way of emphasising the need for a more experimental approach in some areas of the discipline, and that 'control' contains connotations of a highly designed experiment (e.g. with random allocation of subjects to treatments), we use the word counterfactual throughout this report. This should not be taken to mean that rigorous design is not possible in the types of experiments discussed here, but the topic of the usage of the NPMS as a counterfactual is much more closely aligned to the desire to improve existing environmental monitoring in an incremental way, based on what is achievable given practical constraints (including fashion in science and policy), rather than to the topic of designed experiments.

A key consideration then, for any long-term monitoring scheme, is whether the collected data may be useful in providing information on long-term trends, e.g. in populations or communities, that can be used to answer a range of scientific questions. Such questions may focus on the effectiveness of interventions, or other types of change (e.g. neglect or purposeful destruction), between sites that can be assigned to different categories (e.g. managed/unmanaged, protected/unprotected), or which exist along a gradient (e.g. fire frequency).

In this review, we consider the general lessons learnt from a recent attempt to use National Plant Monitoring Scheme (NPMS) data to provide a counterfactual for an independent survey of the effectiveness of Higher-Level Stewardship agri-environmental scheme interventions between two time points (Staley *et al*. 2019). The related issue of assessing value for money of interventions is not discussed further here (see Ferraro & Pattanayak 2006, for discussion of this topic).

3.4.2 General considerations for the effectiveness of the counterfactual approach

Duncan and Vesk (2013) note that the counterfactual is essentially a type of “BACI”, or Before-After, Control-Impact experiment; a type of design that was thoroughly explored as an experimental approach by Underwood (1991). (Note that the use of the word ‘experiment’ here is related to the contention of Underwood (1990) that “all intrusive management or environmental intervention is a form of experiment.”) The effectiveness of this general approach can be seen to be directly related to the clarity with which a researcher is able to specify the set of observations, models, hypotheses and null hypotheses which pertain to any particular experiment (Underwood 1990). This statement is dense with philosophical and practical implication and deserves to be unpacked, so that its relevance to the counterfactual approach is as clearly understood as possible.

Observations

In the case of the management counterfactual, the observations are likely to link to pre-existing models of nature, rather than novel observations for which an investigator would like an explanation. Such observations are likely to be of the form ‘habitat type X has more of its characteristic species when it is managed in this way than in some other way’. Models, hypotheses, and associated experimentation may also need to take into account the fact that motivating observations may be biased or limited. Although this point may be of wider relevance to management or other interventions, it is a general point for experimentation, and is not specifically tied to the use of a counterfactual (Underwood 1990).

Models (theories)

Both Underwood (1990) and Ferraro (2009) consider that models (i.e. theories) underpin the development of testable hypotheses. The place of this process in highly controlled experiments is clear; for more diffuse interventions of the type for which the counterfactual has been considered, the link between models and hypotheses may be less clear. For example, what specific model does an interest in the effect of protected areas entail? If the hypothesis that one desires to test is that habitat X is of a higher quality inside compared to outside of protected areas, is this based on a model of differential management, and if so, of what type? Although a vague model of difference in one direction or another may be satisfactory for some purposes, we should nonetheless recognise that the vaguer the model, the less likely the results are to be useful in other situations. For example, a demonstration of the effectiveness of protected areas may arise from an appropriate counterfactual, but this may still leave the precise ecological (and/or socio-economic) mechanism unknown.

Hypotheses

Hypotheses follow from models. As detailed above, more clearly specified models will provide hypotheses that allow critical feedback to the model. Although vague models of difference between treatments will yield the hypothesis that habitat X under treatment A has more species than X under treatment B, this may not provide transferable information or useful feedback on the model.

Null hypotheses

These are the statistical test hypotheses implied by the hypotheses arising from the model. Underwood (1990) notes that issues of statistical error (type I and type II) can combine with issues of model specification to create a number of ways in which conclusions from experiments may be in error; readers are referred to Underwood (1990) for a clear exposition of these situations.

Experiments

In the case of the counterfactual, the experiment is a management intervention, or other event (e.g. a fire, or other disturbance), that one would like to learn something about. Assuming that one does not have access to a designed, focused experiment with which to try to answer one's ecological questions, an alternative way of learning is to monitor other sites, matched for as many variables as possible, but which have not experienced the event of interest (Underwood 1991). Other relevant variables that are not matched between sites may be accounted for in a statistical model that assumes some parametric relationship between the independent variables and the response (Lele 2010).

It is worth quoting Underwood (1990) in full on the potential value of this approach if adopted widely:

> "[T]here would … be the realization that all intrusive management or environmental intervention is a form of experiment. Construction of well-argued models and hypotheses leading to these experiments would also make it more likely that we could build in some controls [i.e. a counterfactual of some sort], some evaluation after the practice of management (or development) has occurred … and, perhaps, use these situations to learn about spatial and temporal scales beyond the reach of most 'academic' ecologists. We could also, without doubt, learn about the processes operating in these areas of environmental concern and those operating in the minds of environmental and resource managers which led to the particular models being employed. Finally, beyond any shadow of doubt, we could learn from our previous mistakes, because the experimental perturbations of the environment would be in a framework in which their outcomes could be used to evaluate the models that underpin the policies and practices."

Conclusions

From this discussion, it will be seen that the use of data from a long-term monitoring scheme to provide tests of particular ecological models presents two possible options, each with its weaknesses. These weaknesses may be unavoidable if the primary motivation of a monitoring scheme is 'surveillance' or 'omnibus' monitoring, e.g. for the production of national-level indicators.[2]

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[2]This is not to decry this type of descriptive monitoring, but it is an acknowledgement that different approaches have their own strengths and weaknesses relating to their fundamental aims (Pescott *et al.* 2015). Surveillance monitoring is still underpinned by conceptions of what it is important to know, and does not primarily exist for the falsification of model-based hypotheses (although the power to correctly reject a null hypothesis of no change in a population or community will still be an important consideration, even if this does not directly lead to the modification of ecological theory). We should also recall the point of Underwood (1990) above, that the spatial

- The first option is the use of data from a monitoring scheme in isolation. Thus, the ‘control’ (i.e. counterfactual) and ‘impacted’ sites arise from within the set of sites monitored in the programme. For example, NPMS plots inside and outside of protected areas could be compared. The key weakness here is that the surveillance scheme, by definition, will not have been designed with this particular comparison in mind, and therefore the test will necessarily be weaker than an experiment designed particularly to focus on the question of interest.
- The second option is the use of data from one monitoring scheme(s) solely as the control (or impacted) set, with the opposite comparator data arising from a second monitoring dataset. The considerations necessary for, and the related potential weaknesses of this approach, are discussed in detail in the following section (section 3.4.3).

A more complex extension of the second option, which is not explored in great detail here, is for the counterfactual to consist of two separate datasets. This situation might arise where a single long-term study had monitored one type of site (e.g. sites receiving AES options), but there was no single comparator that spanned the entire period covered by the impacted sites (i.e. a BACI design, but where the ‘before’ and ‘after’ control sites come from two separate surveys).

In such a situation, change could be examined between two separate counterfactual datasets covering the same period. This strategy has been used to examine the impacts of higher-level AES in England (Staley *et al*. 2019). The two datasets used as counterfactuals were the 2007 Countryside Survey (Carey *et al*. 2008) and the 2015/2016 NPMS dataset. Such a comparison clearly requires further assumptions regarding the sampling domains of the two surveys: factors which increase variance between the two surveys (e.g. differential skill levels between surveyors in the two periods) will serve to mask the true situation outside of impacted sites.

3.4.3 Confounding variables to consider for the use of the NPMS as a counterfactual

This section deals with the use of the NPMS as a counterfactual for a separate dataset, rather than the use of the NPMS dataset to quantify particular interventions within itself (i.e. the separation of NPMS data into two or more sets, or along a gradient, to investigate a particular question of interest for which the survey was not explicitly designed). The following sub-sections deal with a number of issues that must be considered when seeking to use the NPMS in this way.

Time periods (baselines)

In general, one would want any counterfactual to be located as close as possible in time to the intervention of interest. The further apart the counterfactual and the treatment sites in time, the more likely that other, confounding factors, will account for differences between sites. Apart from the, rather special, situation described at the end of section 3.4.2, in the future the annual nature of the NPMS should mean that this is not an issue for new interventions requiring a counterfactual.

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and temporal scales learnt about through such exercises are those that would likely be “beyond the reach of most ‘academic’ ecologists”, and we have a duty to attempt to extract the most value and information from such datasets. As Pescott *et al*. (2015) point out “volunteer-based surveillance monitoring enables the net to be cast wide for relatively few resources”.

Landscape context

The NPMS dataset is intentionally biased toward 1 km squares with larger areas of nationally rare Land Cover Map (LCM) semi-natural habitat types (Pescott *et al*. 2014a). This is measured by a score calculated for each UK monad; these scores were used to generate a weighted-random draw of NPMS squares for adoption by volunteers (see Pescott *et al*. 2019, for more detail). Ideally then, locations subject to some management or other intervention for which a counterfactual was required would be representative of a similar set of NPMS LCM 1 km square weights. Similar square weights would be required to ensure that the two sets of locations (control and impacted) were representative of similar landscape contexts (the alternative would be to incorporate some indicator of landscape context, thought to be important to the result of interest, into the statistical model used).

Habitats (plant communities)

Equivalence in baseline plant communities will clearly be essential for comparative purposes. In order to support the use of NPMS plots for counterfactual purposes, NPMS habitats have been defined in terms of NVC and EUNIS level 2 and 3 classifications. See http://www.npms.org.uk/content/conservation-and-research for the correspondence tables. Establishing habitat equivalence for counterfactual purposes is a fine art: too narrow a definition of the habitat of interest will likely restrict sample size, and so statistical power; too broad a definition could result in the inclusion of plots that are not likely to be representative of likely change that impacted habitats would have undergone in the absence of the relevant experimental treatment.

Spatial sampling methodology

By 'spatial sampling methodology' we mean the process whereby surveyors locate plots. The NPMS process is described in the NPMS handbook[3]. Briefly, volunteers are presented with up to 25 preselected locations within their adopted 1 km square, located at the intersections of an overlaid fixed grid (Figure 11). Volunteers visit these locations and attempt to record around three square and two linear plots where these coincide with semi-natural habitats, with the aim of recording as many different habitats as possible. Square plots are recorded at intersections of the grid, as described above (numbered plots in Figure 11). Linear habitats are recorded where habitats cross grid lines (demonstrated by the red stars in Figure 11). This method was designed to minimise surveyor bias in plot placement, with the ultimate aim of making collected plot data representative of its respective sampling frame (i.e. all land parcels broadly identifiable as a form of the target habitat). If these methods fail, surveyors are allowed to fall back on subjective methods of plot selection. Specific uses of NPMS data would therefore benefit from an assessment of the proportion of plots that can be identified as having been set up following the less biased primary protocol.

[3] https://www.npms.org.uk/sites/default/files/PDF/NPMS_Survey%20Guidance%20notes_WEB_2ndEd.pdf

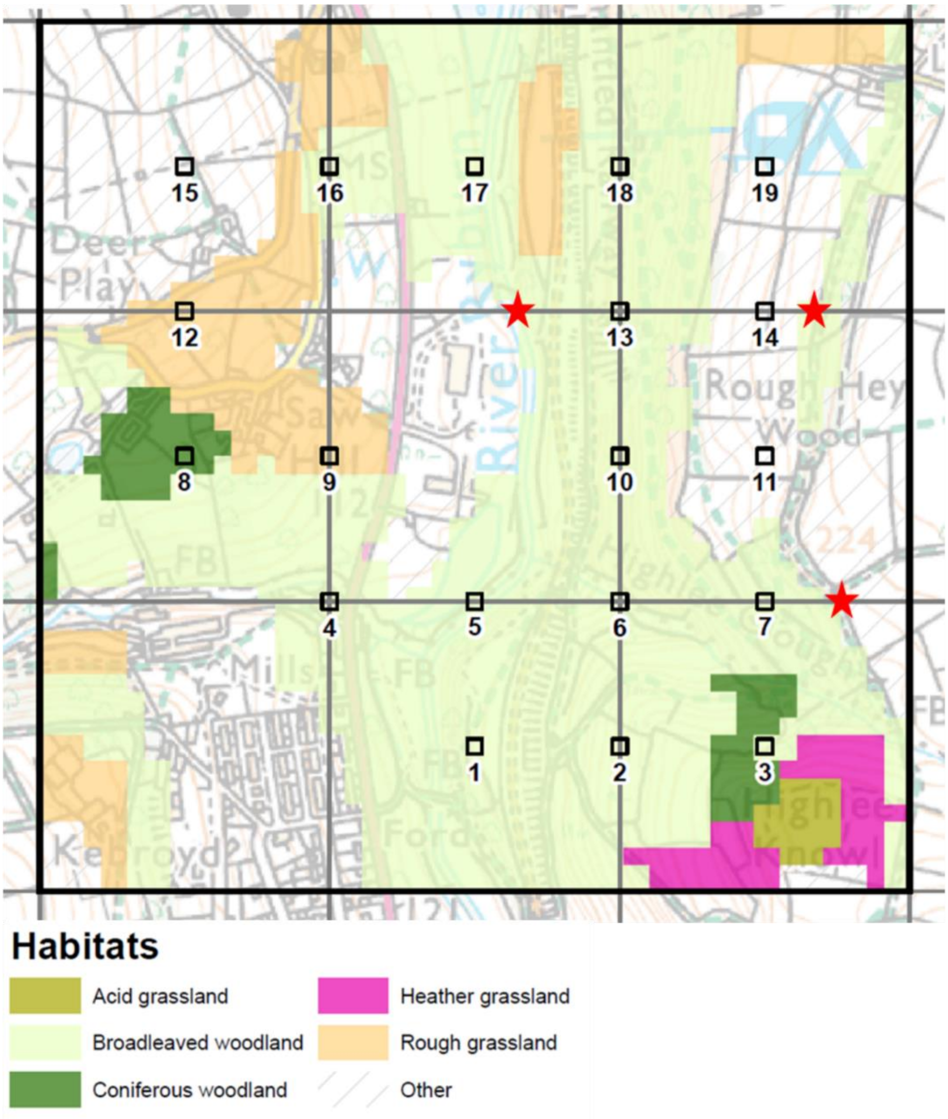

Figure 11. Example of a NPMS 1 km square showing the locations of randomly selected plot locations in relation to semi-natural habitats.
The possible locations of three accessible linear plots along margins of arable fields or water-bodies are also indicated with red stars.

For comparative purposes then, plots from impacted sites should also be selected according to some unbiased methodology (see Maskell *et al*. 2008 for another example of an unbiased protocol for broad habitat-based plot selection).

Plot size

Plot size is another issue that has the potential to affect the species recorded in any particular habitat, and therefore to affect the use of NPMS data as a counterfactual. In the NPMS most plots are 5 x 5m, with the exception of linear habitats and woodlands (Table 16). These sizes were chosen after consultation and field workshops with volunteers and were not primarily chosen for compatibility with other surveys.

Table 16. Plot sizes in NPMS, CS and HLS surveys. See Maskell et al. (2008) for more info on CS plots.

Survey	Linear features	Area features
NPMS	1 × 25 m	5 × 5 m, 10 × 10 m in woodland, 2 × 12.5 m on slopes, screes and in some wetlands and water bodies.
Countryside Survey (CS)	1 × 10 m, 1 × 1 m in 'M' plots in field margin strips; 1 × 1 m central plot in arable field margins.	Nested 'X' plots that include 1 × 1 m, 5 × 5 m and 10 × 10 m sizes.
Higher Level Stewardship (HLS) surveys	1 × 1 m plots in arable field margins only. No other linear features surveyed.	1 × 1 m in all habitats except 4 × 4 m (bog, dwarf shrub heath, fen marsh & swamp) and 10 × 10 m in woodland.

Given that the number of species recorded does not typically have a linear relationship with area (Fridley *et al*. 2006), the comparison of NPMS data with data from plots of different sizes in other schemes should be carefully approached. Although it is clearly desirable to only compare plots of the same size between datasets, we note that other researchers have used non-linear curve-fitting to estimate empirical species-area relationships in datasets in order to make adjustments to plot areas to facilitate comparisons (Fridley *et al*. 2007). Of course, each such adjustment can be seen to introduce an extra element of uncertainty. This is particularly the case if the metric to be compared depends on cover, rather than just the presence or absence of species (e.g. cover-weighted Ellenberg metrics).

Species coverage and observer bias

Observer skill and survey remit both have the potential to affect recording coverage. NPMS surveyors can participate at any one of three levels of botanical knowledge, and at one of two levels of habitat discrimination; both these elements can vary by plot. That is to say, a surveyor is free to choose both the survey level (affecting the number of species sought) and the habitat resolution (likewise) for each of their plot surveys. Apart from the obvious aspect of asking people to search for and report on subsets of the total set of species present in a plot, surveyor skill may also affect the number of species detected. Both in terms of surveyors missing species that are in fact present, and the possibility that they report species that are actually absent (e.g. through misidentification, or errors in name recall and transcription). Clearly, the use of the NPMS as a counterfactual should take the possibility of these types of bias into account, and only use appropriate subsets for comparisons. It is possible that a greater understanding of these bias-inducing processes could also lead to the possibility that NPMS data could sometimes be adjusted in compensation.

Staley *et al*. (2019) made efforts to quantify such potential biases in their attempt to use both NPMS and Countryside Survey data to produce a counterfactual for the Higher-Level Stewardship AES in England. A graphical exploration of NPMS and data collected according to Countryside Survey protocols under the Glastir Monitoring and Evaluation Project (www.gmep.wales) has indicated that NPMS Indicator-level plots (the 'intermediate' level in the NPMS) were consistently poorer in NPMS indicator species[4] than GMEP and NPMS Inventory-level plots (the 'full survey' level of the NPMS). Indicator-level plots were therefore excluded from this analysis given that there was evidence for underestimation of indicator richness in these plots (Staley *et al.* 2019).

This was not unexpected given that NPMS Indicator-level recording will tend to attract those volunteers less able to confidently census all species; these surveyors are likely to have

[4] In the NPMS, lists of species are provided for surveyors in relation to the habitat and level at which they are participating. At the Indicator survey level, the sets of species are termed 'indicator species'.

recorded on average fewer indicator species than are present in Inventory-level plots for which a full census is recorded. In addition, NPMS Inventory plots were, on average, more species rich than the fully censused GMEP plots; this may have been related to surveyor bias in plot placement (no bias relating to landscape context was detected). In this case, so as to maintain consistency of recording across the GMEP and NPMS datasets (i.e. to remove the effect of both under recording in the Indicator plots and to reduce the effect of bias in the Inventory plots), all response variables analysed were calculated based on presence of NPMS indicator species only.

Experiment-specific considerations

In relation to any particular counterfactual, attention must be paid to past land uses that are likely to affect the result. For example, NPMS plots to be used as a counterfactual for AES would ideally not have been in an AES themselves in the recent past; legacy effects of such management could otherwise reduce or remove the intended difference between the counterfactual and the impacted sites. This guidance is little different to advising an appreciation of historical processes in any ecological research (Rackham 1998), but it seems possible that this type of phenomenon may be rarely considered when constructing counterfactuals. If information on a particular variable of importance is discovered, then statistical tests of the variable within the counterfactual data could be used to determine whether plots with historical legacies should be excluded from analyses.

3.4.4 Conclusions

Ferraro (2009, pg. 81) notes that, in general, the “reliability [of conclusions] depends on the analyst’s ability to specify the counterfactual”. This is likely to be particularly true when controls are not built into an investigation from the start. Success in erecting an appropriate counterfactual then, depends largely on the possibility of constructing a comparator dataset that differs from the ‘impacted’ sites in terms of the treatment only, and that all other differences are minimised. This is to say, variables that have the potential to confound a treatment effect should be eliminated, or, where this is not possible, identified and included in statistical models.

Given this, as scientists researching the consequences of policy decisions, we might reasonably ask whether an ecological evaluation of programmes that do not have comparators built-in is an efficient use of funds. More focused experiments might reveal more about the management techniques of interest.[5] However, we should recall that schemes such as the NPMS are primarily designed to provide an overview of habitat status and trends (and to produce national level indicators), and that additional uses that can be found for the collected data, such as use as a counter-factual, are additional benefits.

As was noted above, the key advantage of counterfactual designs for understanding changes across landscapes is perhaps the access to processes that would be unlikely to be accessible to the average experimentalist. Carefully chosen counterfactuals can yield information that would be unlikely to be accessed in any other way. Schemes such as the NPMS can be useful in this situation, given that they aim to sample widely across the landscape, albeit with some known, and some unknown, biases towards semi-natural habitats and richer plant communities. Efforts to properly match NPMS data to sites is required to produce a counterfactual that will ensure that conclusions are as clear as is possible; likewise, clearly specified models, as in all areas of ecology, will increases the chance that conclusions will provide useful insights into land management or other ecological processes.

[5] Note that, in cases such as agri-environmental stewardship, monitoring of implementation itself would most likely still be required, because that is also a socio-economic issue.

3.5 The NPMS and Earth Observation ground-truthing

A range of EO products exist and are planned. An essential component of any such surveys is calibration of the remote sensing images and ground truthing. This section discusses how NPMS data could be used in this context.

One such EO product is the latest CEH Land Cover Map based on 2015 data. Comparison of LCM with NPMS was carried out to evaluate the degree of correspondence between the two datasets. It is concluded that NPMS could offer additional information, for instance in distinguishing closely related habitats and picking out features too small to be distinguished at the scale of the LCM.

Bog and wet heath habitats were used as a case study to illustrate the degree of correspondence between the two datasets, and how the finer scale NPMS could be used to improve LCM.

It was concluded that information collected by NPMS surveyors for transitional habitats would be of particular value in the context of EO, particularly when combined with increasingly fine-scale EO data. Reciprocal benefits for the NPMS are also acknowledged.

As increasingly fine-scale EO data is produced, we need to consider, among other aspects, how NPMS data could feed into EO based assessments of habitat condition.

3.5.1 Introduction

As Earth Observation (EO) increases in its discriminatory power, both in terms of its spatio-temporal resolution, and in terms of the processing of such data into useful land-cover classifications, there is increasing interest in its use for assessing habitat quality. In the context of Common Standards Monitoring, for example, quality is usually defined in relation to habitat attributes, which are “characteristics of an interest feature that describe its condition, either directly or indirectly” (JNCC 2004). Such attributes may cover many variables, such as aspects of habitat structure and function; often, however, they are also defined in terms of habitat correspondence. For example, JNCC state that “[t]he National Vegetation Classification (NVC) is one of the key common standards developed for the [UK’s] country nature conservation agencies” (http://jncc.defra.gov.uk/page-4259). This implies that community stasis and change are a key part of assessing quality (Pescott & Roy 2016).

Leaving aside those elements of habitat condition relating to structure, or other non-community focused aspects (see section 2.3), a useful first step in assessing the potential of NPMS plots to inform existing or new EO products is to cross-compare the NPMS habitats that surveyors report for their plots with a current EO product covering the same spatial domain. The recent release of the CEH Land Cover Map 2015 (LCM 2015; Centre for Ecology & Hydrology 2017) is useful for this purpose. The LCM 2015 has a minimum mappable unit of 0.5 hectares (around 70 x 70 metres) and covers the whole of Britain and Northern Ireland (excluding the Isle of Man and the Channel Isles, which are covered by the NPMS). This comparison should highlight where the NPMS offers additional information not covered by the LCM 2015. We anticipate that NPMS information will be particularly useful in distinguishing closely related habitats, e.g. heathland and acid grassland at fine scales, and in picking up small features within larger areas of habitat (e.g. acid flushes within grassland).

We expect that future work in this area would work with higher resolution EO datasets subject to more finely-divided classifications, with the NPMS again providing the plant community (and also structural) information collected by surveyors to assist with the validation of such schemes. In fact, NPMS data is currently being used in the production of the Living England Map to train and validate classification of EO data. This is an initiative led by Natural England in collaboration with the JNCC, to produce detailed habitat maps. Hierarchical or other modelling approaches could also be used to combine EO predictions and fine-scale plot information, contributing to assignment probability scores, such as those associated with some LCM 2015 products (Centre for Ecology & Hydrology 2017).

3.5.2 Can NPMS habitat classifications improve existing land cover products?

Methods

As a rapid assessment of the likely potential of NPMS sample data to add value to land cover products, British NPMS plot sample data for 2015 and 2016 were extracted along with their surveyor-attributed broad- or fine-scale habitats and locations. Using a correspondence table establishing links between NPMS habitat types and the Land Cover Map 2015 types (Annex 3), the LCM 2015 land covers for NPMS plot locations were extracted using a geospatial database query and cross-tabulations assembled.

Results

Three tables are presented. Table 17 gives the cross-tabulation for British NPMS 2015 and 2016 plots with the LCM 2015 for plots recorded at the NPMS broad-scale habitat level only; Table 18 presents this for all plots, with fine-scale NPMS habitats nested within their appropriate broad-scale habitat; Table 19 provides this information for plots recorded at the NPMS fine-scale only.

In general, one would expect greater correspondence between NPMS habitats recorded at the broad level with the LCM 2015. Habitats recorded at the broad level by volunteer surveyors are more likely to be correct than fine-scale attributions, given the reduced discrimination demanded of the surveyor. There is also less room for disagreement between the LCM 2015 and NPMS broad classifications than there is between the LCM 2015 and the NPMS fine-scale classification (Annex 3). This appears to be borne out by Table 17: there are in general fewer NPMS samples at this level (most surveyors preferring to identify a plot to the fine-scale level), but there is less divergence between the NPMS recorded habitats and the LCM 2015 compared to when fine-scale NPMS habitats are included within their corresponding broad-scale habitat (Table 18).

Table 18 provides a concise way of evaluating all of the correspondences between the 2015/16 NPMS plots and the LCM 2015. Note here that we have not grouped LCM 2015 habitats to produce a better correspondence to NPMS broad habitats, e.g. the LCM's calcareous grassland is presented as a separate cover type, whereas for the NPMS broad habitats dry calcareous grassland has been grouped under its broad habitat type, lowland grassland.

Table 19 gives the full table for NPMS plots recorded at the fine-habitat scale. Note that the NPMS habitats that show the most scatter across LCM 2015 types are those that are likely to be small features embedded within other land cover types (e.g. acidic and base-rich flushes, nutrient-rich or -poor waterbodies). The scatter associated with some linear features in the NPMS data may be due to the spatial references for linear NPMS plots being erroneously attributed to the adjacent land cover type (e.g. rivers and streams to improved grassland).

3.5.3 Overall conclusions

Data collected by volunteer surveyors under the National Plant Monitoring Scheme appear to add useful fine-scale detail in relation to a, relatively coarsely classified, EO product such as the LCM 2015. Of course, we should not forget that habitat classifications within the NPMS have not been subject to quality assurance surveys (section 1.4), or any other type of review; however, for generally unmistakeable habitats, such as hedgerows, the contributions from the NPMS to the LCM 2015 are clear. For this example, this is not surprising: the CEH Land Cover Map products have never included hedgerows, although separate, hedgerow-specific, products have been created for limited areas of the country for other projects (J. Redhead, pers. comm.) In addition, the separation of closely similar types (e.g. flushes in acid grassland or wet heath), may not be possible without spatio-temporal resolutions of a higher degree to those used for the LCM 2015; the minimum mappable unit of the LCM 2015 is 0.5 of a hectare.

Finally, we briefly discuss the correspondences discovered for a single NPMS broad class and its nested fine-scale habitats, specifically, the bog and wet heath NPMS broad habitat.

Bog and wet heath

The fine-scale NPMS habitats within this broad category (blanket bog, raised bog, wet heath) can often be difficult to separate, based as they are on local topography and peat depth. We might expect both the LCM 2015 and NPMS surveyors to have issues classifying them (Centre for Ecology & Hydrology 2017). The LCM 2015 guidance (CEH 2017) points out that “[t]he division in the field [by a surveyor] can account for species presence, plus peat depth, but for LCM 2015 the division is based on the spectral data and presumably [sic.] also the slope data”. Indeed, as the LCM 2015 guidance also notes, the separation between acid grassland types, bog, dwarf shrub heath types and embedded flushes can be very challenging. Table 17 bears this out: more NPMS plots broadly-classified as ‘bog and wet heath’ are classified as other types of LCM habitat than as ‘bog’ (29 v. 13). Of those classified as other than bog, acid grassland (7) and heather/heather grassland (8 combined) are the most common, although improved grassland is also a frequent conclusion of the LCM 2015 (7). It may be that these plots are in more degraded types of bog with a high grass cover (e.g. *Molinia caerulea*, *Nardus stricta*, *Agrostis canina etc*.) Other ‘confusion’ habitats are coniferous woodland, arable and saltmarsh. These may be due to adjacent habitat or habitat in rides, machair transitions (i.e. arable on landward machair), and ecotones respectively, although we have not investigated the individual NPMS plots nor the LCM 2015 locations in detail.

Table 18 includes all of the NPMS fine-scale plots within the broad-scale cross-tabulation. This table, including as it does NPMS plots recorded as either bog and wet heath, blanket bog, raised bog or wet heath, contains a greater degree of scatter in correspondence with the LCM 2015. The number of plots classified as acid grassland by the LCM 2015 increases markedly, as do those in coniferous woodland, heather/heather grassland, and improved grassland. Arable, saltmarsh, neutral grassland, suburban and littoral rock all also make an appearance, although, with the exception of arable (4), these are limited to one plot each. We expect that these are all due to ecotonal variation at small scales; the plot classified as suburban looks to be due to a small area of wet woodland in south Wales, apparently containing an area of wet heath, being encircled by housing.

Table 19 provides a full breakdown of the NPMS fine-scale plots, allowing for a more detailed examination of some of the LCM correspondences discussed above. These data show that raised bog plots are rare in the current NPMS British dataset, and none of the three recorded locations were identified as bog by the LCM 2015. This seems to be due to either small areas of raised bog being recorded within larger areas of wet heath/acid grassland, or to lowland raised bog that has a history of horticultural use (e.g. Westhay Moor NNR, Somerset). Blanket bog is the NPMS fine-scale type most likely to be classified correctly (assuming that the NPMS classifications are accurate) by the LCM 2015. As discussed above, confusion with acid grassland, coniferous woodland, heather/heather grassland and improved grassland still feature (and arable and saltmarsh to a much lesser extent).

As might be expected, given the intergradation of the habitat with other land cover types, wet heath was subject to spread across several LCM 2015 categories. Seven plots were attributed to the LCM bog class, whilst heather/heather grassland was much more frequent (a total of 37 plots), and acid grassland was also a common conclusion (16 plots). Indeed, the LCM 2015 states that this division is challenging, and that only spectral information and, seemingly, topographic information were used. It is in fact difficult to know exactly where wet heath should sit within the LCM 2015 classification: heather/heather grassland make no explicit mention of other ericaceous subshrubs (e.g. *Erica tetralix*) on shallow peats, whilst the bog class is reported to exclude vegetation on shallow peat. It may be that information collected by NPMS surveyors for such transitional habitats is of considerable value in the context of EO, particularly when combined with increasingly fine-scale EO data. This could have reciprocal benefits for the NPMS: one could imagine EO data being used to classify the locations of existing NPMS wet heath plots, with this information, appropriately contextualised, being fed back to volunteers. This might also help to focus attention on “boundary” plots that were considered particularly likely to change NPMS habitat by virtue of their presence at one of the boundaries in plant community space.

Table 17. A cross-tabulation showing the coincidence of particular LCM 2015 cover types with British NPMS plots recorded by surveyors in 2015/16 at the broad habitat level.
Note that the colours are scaled arbitrarily and are only intended to draw the eye to those cells with data in the table.

	NPMS Broad-scale habitat								
LCM2015	Bog and wet heath	Broadleaved woodland, hedges and scrub	Coast	Freshwater	Heathland	Lowland grassland	Marsh and fen	Native pinewood and juniper scrub	Upland grassland
Acid grassland	7	1	0	3	4	13	2	0	7
Arable and horticulture	2	27	0	3	1	36	3	0	0
Bog	13	0	0	1	4	4	2	0	0
Broadleaf woodland	0	76	1	4	0	17	4	0	0
Calcareous grassland	0	1	0	0	0	3	0	0	0
Coniferous woodland	4	8	0	0	1	4	0	6	2
Fen, marsh and swamp	0	0	0	1	0	0	2	0	0
Freshwater	0	1	1	3	0	3	0	0	0
Heather	2	0	0	0	21	0	2	0	0
Heather grassland	6	0	0	0	2	3	0	0	2
Improved grassland	7	33	2	5	3	92	8	0	0
Inland rock	0	1	0	0	0	0	0	0	0
Littoral rock	0	0	1	0	0	0	0	0	0
Littoral sediment	0	0	5	0	0	2	0	0	0
Neutral grassland	0	1	2	3	0	3	1	0	0
Saltmarsh	1	0	4	0	0	2	0	0	0
Saltwater	0	0	0	0	0	0	0	0	0
Suburban	0	7	3	0	0	8	2	0	0
Supralittoral rock	0	0	1	0	0	3	0	0	0
Supralittoral sediment	0	0	3	0	0	7	1	0	0
Urban	0	1	0	0	0	0	0	0	0

Table 18. A cross-tabulation showing the coincidence of particular LCM 2015 cover types with British NPMS plots recorded by surveyors in 2015/16 at the broad and fine habitat levels.
The fine-scale records have been nested in their appropriate NPMS broad habitat. Note that the colours are scaled arbitrarily and are only intended to draw the eye to those cells with data in the table.

	NPMS Broad-scale (including nested fine-scale) habitats											
LCM2015	Arable margins	Bog and wet heath	Broadleaved woodland, hedges and scrub	Coast	Freshwater	Heathland	Lowland grassland	Marsh and fen	Native conifer woods and juniper scrub	Not in scheme	Rock outcrops, cliffs and scree	Upland grassland
Acid grassland	0	36	12	1	12	25	45	16	0	0	12	34
Arable and horticulture	196	4	177	12	17	5	98	9	0	10	2	0
Bog	0	30	0	0	2	15	4	5	0	0	1	2
Broadleaf woodland	0	1	356	8	31	7	61	8	5	3	6	3
Calcareous grassland	0	0	7	1	3	0	23	0	0	0	0	0
Coniferous woodland	0	17	19	2	3	11	16	3	31	2	2	6
Fen, marsh and swamp	0	0	0	0	2	0	1	3	0	0	0	0
Freshwater	0	0	6	4	15	0	7	2	0	0	1	0
Heather	0	18	3	2	6	63	5	11	0	1	1	3
Heather grassland	0	39	4	0	5	25	25	15	0	1	3	7
Improved grassland	31	16	270	8	65	20	453	30	1	12	5	3
Inland rock	0	1	2	0	0	0	1	1	0	0	2	2
Littoral rock	0	0	0	2	0	0	0	0	0	0	1	0
Littoral sediment	0	0	0	32	0	0	3	0	0	0	1	0
Neutral grassland	0	1	6	2	5	0	13	4	0	0	0	0
Saltmarsh	0	1	6	33	6	0	11	0	0	0	0	0
Saltwater	0	0	0	2	0	0	0	0	0	0	0	0
Suburban	0	1	42	3	6	1	35	6	0	1	1	0
Supralittoral rock	0	1	1	10	0	1	7	0	0	0	2	0
Supralittoral sediment	0	0	2	32	4	2	13	2	0	1	0	0
Urban	0	0	11	16	1	0	2	0	0	4	1	0

Table 19. A cross-tabulation showing the coincidence of particular LCM 2015 cover types with British NPMS plots recorded in 2015/16 by surveyors at the fine habitat level. Note that the colours are scaled arbitrarily and are only intended to draw the eye to those cells with data in the table.

	NPMS Fine-scale habitat												
LCM2015	Acid fens, mires and springs	Arable field margins	Base-rich fens, mires and springs	Blanket bog	Coastal saltmarsh	Coastal sand dunes	Coastal vegetated shingle	Dry acid grassland	Dry calcareous grassland	Dry deciduous woodland	Dry heathland	Hedgerows of native species	Inland rocks and scree
Acid grassland	13	0	1	13	0	0	0	15	7	4	19	6	2
Arable and horticulture	4	196	2	0	1	0	1	2	14	29	4	118	1
Bog	2	0	1	10	0	0	0	0	0	0	8	0	0
Broadleaf woodland	0	4	4	0	0	0	7	7	3	210	6	22	5
Calcareous grassland	0	0	0	0	0	0	0	0	20	3	0	2	0
Coniferous woodland	2	1	1	4	0	2	0	7	1	10	10	1	1
Fen, marsh and swamp	0	0	1	0	0	0	0	0	0	0	0	0	0
Freshwater	0	0	2	0	1	0	2	0	0	4	0	1	1
Heather	6	0	3	4	0	0	0	1	2	2	38	1	0
Heather grassland	14	0	1	7	0	0	0	7	0	3	23	0	2
Improved grassland	8	31	14	1	2	0	1	25	69	58	17	170	5
Inland rock	0	0	1	0	0	0	0	0	1	1	0	0	0
Littoral rock	0	0	0	0	0	0	0	0	0	0	0	0	1
Littoral sediment	0	0	0	0	5	8	14	0	1	0	0	0	0
Neutral grassland	3	0	0	0	0	0	0	1	3	2	0	3	0
Saltmarsh	0	0	0	0	25	2	2	1	0	0	0	5	0
Saltwater	0	0	0	0	1	0	1	0	0	0	0	0	0
Suburban	0	5	4	0	0	0	0	1	3	17	1	14	1
Supralittoral rock	0	0	0	0	2	0	2	2	1	0	1	0	2
Supralittoral sediment	0	0	1	0	2	16	5	3	1	0	2	2	0
Urban	0	1	0	0	3	1	9	0	0	4	0	6	1

Table 19 (continued).

LCM2015	NPMS Fine-scale habitat (cont.)													
	Maritime cliffs and slopes	Montane acid grassland	Montane calcareous grassland	Montane dry heathland	Native conifer woods and juniper scrub	Neutral damp grassland	Neutral pastures and meadows	Not in scheme	Nutrient-poor lakes and ponds	Nutrient-rich lakes and ponds	Raised bog	Rivers and streams	Wet heath	Wet woodland
Acid grassland	1	21	6	2	0	4	6	0	3	0	0	6	16	1
Arable and horticulture	10	0	0	0	0	9	37	10	2	8	2	4	0	3
Bog	0	1	1	3	0	0	0	0	1	0	0	0	7	0
Broadleaf woodland	0	3	0	1	5	14	20	3	3	9	0	15	1	48
Calcareous grassland	1	0	0	0	0	0	0	0	2	0	0	1	0	1
Coniferous woodland	0	4	0	0	31	3	1	2	0	0	0	3	9	0
Fen, marsh and swamp	0	0	0	0	0	1	0	0	0	1	0	0	0	0
Freshwater	0	0	0	0	0	3	1	0	4	7	0	1	0	0
Heather	2	2	1	4	0	2	0	1	2	0	0	4	12	0
Heather grassland	0	5	0	0	0	11	4	1	3	1	1	1	25	1
Improved grassland	3	1	2	0	1	63	204	12	4	21	0	35	8	9
Inland rock	0	0	2	0	0	0	0	0	0	0	0	0	1	0
Littoral rock	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Littoral sediment	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Neutral grassland	0	0	0	0	0	4	2	0	0	0	0	2	1	0
Saltmarsh	0	0	0	0	0	6	2	0	1	3	0	2	0	1
Saltwater	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Suburban	0	0	0	0	0	6	17	1	1	1	0	4	1	4
Supralittoral rock	5	0	0	0	0	1	0	0	0	0	0	0	1	1
Supralittoral sediment	6	0	0	0	0	0	2	1	2	2	0	0	0	0
Urban	3	0	0	0	0	1	1	4	0	0	0	1	0	0

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Annex 1: Power analysis

Well-represented NPMS indicator species (2015/2016)

Table A1.1 below provides plot counts for all NPMS indicator species (both positive and negative), where greater than or equal to 30 for 2015 and 2016. Note that these are counts of actual plot locations where a species has been recorded at least once, irrespective of year or sampling visit. Counts of samples of plots (i.e. plot visits) containing a species will often be larger and can be found in the spreadsheet presented as online appendix 2 under section 1.3 above.

Table A1.1. Counts of unique NPMS plots (i.e. spatially unique locations, regardless of the number of visits) for positive and negative indicator species, where greater than 30. Counts correct for 2015/2016 at the time of reporting.

Taxon	Plot Count	Indicator	Taxon	Plot Count	Indicator
Urtica dioica	972	neg	*Succisa pratensis*	68	pos
Rubus fruticosus agg.	769	neg	*Sonchus asper*	67	pos
Galium aparine	766	neg	*Iris pseudacorus*	66	pos
Ranunculus repens	570	pos/neg	*Narthecium ossifragum*	66	pos
Crataegus monogyna	549	pos/neg	*Campanula rotundifolia*	65	pos
Holcus lanatus	511	pos	*Galium mollugo*	65	pos
Cirsium arvense	457	neg	*Angelica sylvestris*	64	pos
Heracleum sphondylium	442	pos	*Trifolium dubium*	63	pos
Anthriscus sylvestris	430	neg	*Linum catharticum*	61	pos
Hedera helix	424	pos/neg	*Teucrium scorodonia*	61	pos
Trifolium repens	401	pos	*Bromus hordeaceus*	60	pos
Plantago lanceolata	393	pos	*Pilosella officinarum*	59	pos
Potentilla erecta	327	pos	*Conopodium majus*	58	pos
Calluna vulgaris	325	pos	*Carex echinata*	57	pos
Geum urbanum	323	pos	*Helictotrichon pratense*	57	pos
Rumex acetosa	317	pos	*Phyllitis scolopendrium*	56	pos
Cerastium fontanum	304	pos	*Lotus pedunculatus*	56	pos
Pteridium aquilinum	297	neg	*Leucanthemum vulgare*	56	pos
Ranunculus acris	292	pos	*Capsella bursa-pastoris*	56	pos
Anthoxanthum odoratum	250	pos/neg	*Blechnum spicant*	55	pos
Geranium robertianum	249	pos	*Anemone nemorosa*	55	pos
Trifolium pratense	246	pos	*Medicago lupulina*	55	pos
Senecio jacobaea	242	pos/neg	*Ajuga reptans*	54	pos
Prunus spinosa	231	pos	*Allium ursinum*	53	pos
Prunus spinosa	231	neg	*Veronica montana*	53	pos
Glechoma hederacea	231	pos	*Carex panicea*	52	pos
Vaccinium myrtillus	224	pos	*Primula veris*	52	pos
Hyacinthoides non-scripta	216	pos	*Rhinanthus minor*	52	pos
Corylus avellana	206	pos	*Alnus glutinosa*	52	pos
Agrostis capillaris	202	neg	*Clematis vitalba*	51	pos
Galium saxatile	195	pos	*Torilis japonica*	51	pos
Lotus corniculatus	194	pos	*Anagallis arvensis*	51	pos
Ilex aquifolium	193	pos	*Primula vulgaris*	50	pos
Achillea millefolium	193	pos	*Carex flacca*	49	pos
Arum maculatum	175	pos	*Empetrum nigrum*	48	pos

Taxon	Plot Count	Indicator	Taxon	Plot Count	Indicator
Cirsium vulgare	172	pos	*Chenopodium album*	48	pos
Cirsium palustre	169	pos	*Impatiens glandulifera*	47	neg
Silene dioica	164	pos	*Briza media*	46	pos
Juncus effuses	162	neg	*Potentilla sterilis*	44	pos
Bellis perennis	161	pos	*Veronica officinalis*	44	pos
Prunella vulgaris	160	pos	*Sonchus oleraceus*	44	pos
Mercurialis perennis	155	pos	*Carex pendula*	44	pos
Hypochaeris radicata	155	pos	*Tripleurospermum inodorum*	44	pos
Deschampsia flexuosa	151	pos/neg	*Betula pendula*	41	pos/neg
Rumex obtusifolius	149	neg	*Cirsium acaule*	41	pos
Lonicera periclymenum	149	pos	*Calystegia sepium*	41	pos
Digitalis purpurea	142	pos	*Solanum dulcamara*	40	pos
Molinia caerulea	135	pos	*Veronica arvensis*	40	pos
Stellaria graminea	132	pos	*Ammophila arenaria*	39	pos
Erica cinereal	132	pos	*Caltha palustris*	39	pos
Rumex crispus	128	pos/neg	*Drosera rotundifolia*	39	pos
Erica tetralix	125	pos	*Vaccinium vitis-idaea*	39	pos
Cardamine pratensis	123	pos	*Cruciata laevipes*	39	pos
Cynosurus cristatus	122	pos	*Centaurea scabiosa*	38	pos
Epilobium hirsutum	122	pos	*Sonchus arvensis*	38	pos
Ranunculus bulbosus	118	pos	*Alopecurus myosuroides*	38	neg
Stellaria media	118	neg	*Typha latifolia*	37	pos
Filipendula ulmaria	113	pos	*Cornus sanguinea*	37	pos
Juncus squarrosus	110	pos	*Chaerophyllum temulum*	36	pos
Lathyrus pratensis	108	pos	*Alopecurus geniculatus*	35	pos
Stellaria holostea	105	pos	*Lysimachia nemorum*	35	pos
Vicia cracca	105	pos	*Equisetum arvense*	34	pos
Deschampsia cespitosa	105	pos/neg	*Milium effusum*	34	pos
Viola riviniana	104	pos	*Phalaris arundinacea*	34	pos
Oxalis acetosella	103	pos	*Hydrocotyle vulgaris*	34	pos
Eriophorum angustifolium	99	pos	*Aster tripolium*	34	pos
Ulex europaeus	97	neg	*Picris echioides*	34	pos
Circaea lutetiana	94	pos	*Dactylorhiza fuchsii*	34	pos
Nardus stricta	93	pos	*Veronica beccabunga*	33	pos
Rumex acetosella	92	pos	*Origanum vulgare*	33	pos
Potentilla reptans	87	pos	*Cerastium glomeratum*	32	pos
Eriophorum vaginatum	86	pos	*Chrysosplenium oppositifolium*	32	pos
Sorbus aucuparia	83	pos	*Plantago media*	32	pos
Galium verum	83	pos	*Plantago coronopus*	32	pos
Carex nigra	76	pos	*Carex sylvatica*	32	pos
Luzula multiflora	74	pos	*Silene latifolia*	32	pos
Galium palustre	73	pos	*Viola arvensis*	31	pos
Mentha aquatica	68	pos	*Plantago maritima*	30	pos

Other well-represented taxa recorded at Inventory level

Table A1.2 below provides plot counts for all non-indicator species recorded at Inventory level, where greater than or equal to 30 for 2015 and 2016. Note that these are counts of actual plot locations where a species has been recorded at least once, irrespective of year or sampling visit. Counts of samples of plots (i.e. plot visits) containing a species will often be larger and can be found in the spreadsheet presented under section 1.3 above, which summarises across all taxa recorded, regardless of NPMS indicator status or the number of plots.

Table A1.2. Counts of unique NPMS plots (i.e. spatially unique locations) for non- indicator taxa, where greater than 30. Counts correct for 2015/2016 at the time of reporting.

Taxon	Plot Count	Taxon	Plot Count
Dactylis glomerate	256	*Epilobium montanum*	55
Taraxacum	325	*Alopecurus pratensis*	54
Arrhenatherum elatius	174	*Convolvulus arvensis*	54
Poa trivialis	163	*Brachypodium sylvaticum*	54
Rubus	163	*Juncus articulatus*	52
Juncus inflexus/effusus/conglomeratus	157	*Acer campestre*	51
Festuca rubra	156	*Trichophorum caespitosum s.lat.*	51
Rumex crispus/obtusifolius	152	*Lamium galeobdolon*	48
Fraxinus excelsior	146	*Holcus mollis*	47
Lolium perenne	130	*Poa pratensis*	47
Agrostis stolonifera	120	*Polygala serpyllifolia/vulgaris*	47
Veronica chamaedrys	109	*Festuca rubra* agg.	46
Sambucus nigra	95	*Viola reichenbachiana/riviniana*	46
Stachys sylvatica	93	*Fagus sylvatica*	45
Plantago major	90	*Alliaria petiolata*	45
Acer pseudoplatanus	87	*Vicia sepium*	44
Quercus robur	85	*Ranunculus flammula*	43
Poa annua	81	*Myosotis arvensis*	43
Potentilla anserine	79	*Phleum pratense*	43
Geranium dissectum	69	*Luzula campestris*	42
Rumex	69	*Scorzoneroides autumnalis*	42
Rosa canina	68	*Euphrasia*	41
Centaurea nigra	67	*Chamerion angustifolium*	40
Ranunculus ficaria	65	*Agrostis*	39
Dioscorea communis	65	*Elytrigia repens*	38
Dryopteris filix-mas	64	*Veronica persica*	37
Betula pubescens/pendula	63	*Geranium molle*	35
Rumex sanguineus	62	*Crepis capillaris*	35
Lamium album	62	*Epilobium*	34
Vicia sativa	61	*Senecio vulgaris*	33
Dryopteris dilatate	61	*Corylus*	33
Bromus sterilis	59	*Lotus*	32
Festuca ovina	58	*Lolium*	31
Quercus	57	*Phragmites australis*	31
Lapsana communis	56	*Viola*	31

Indicator and Inventory species: Country-level plot representation

The following subsections subdivide the preceding information by country, only retaining taxa where 30 plots or more exist. The data for England are presented first in Table A1.3.

England

Table A1.3. Counts of unique NPMS plots (i.e. spatially unique locations) for taxa in England, where greater than 30. Counts correct for 2015/2016 at the time of reporting. Plots were assigned to England on the basis of their parent 1 km square; where 1 km squares overlap country boundaries, the square was assigned to the country accounting for the largest proportion of its area.

Taxon	Plot Count	Taxon	Plot Count
Urtica dioica	788	*Galium verum*	56
Galium aparine	632	*Bromus sterilis*	55
Rubus fruticosus agg.	626	*Deschampsia cespitosa*	55
Crataegus monogyna	463	*Convolvulus arvensis*	53
Ranunculus repens	389	*Rosa canina*	53
Anthriscus sylvestris	364	*Iris pseudacorus*	52
Hedera helix	358	*Ranunculus ficaria*	52
Heracleum sphondylium	354	*Medicago lupulina*	52
Cirsium arvense	353	*Rumex acetosella*	52
Holcus lanatus	326	*Mentha aquatica*	52
Plantago lanceolate	271	*Acer campestre*	51
Geum urbanum	268	*Leucanthemum vulgare*	51
Trifolium repens	262	*Sonchus asper*	51
Cerastium fontanum	224	*Bromus hordeaceus*	51
Dactylis glomerate	210	*Vicia sativa*	51
Glechoma hederacea	209	*Viola riviniana*	51
Geranium robertianum	196	*Lapsana communis*	50
Prunus spinosa	194	*Capsella bursa-pastoris*	50
Pteridium aquilinum	193	*Quercus*	50
Trifolium pratense	191	*Trifolium dubium*	49
Rumex acetosa	189	*Primula veris*	49
Senecio jacobaea	183	*Centaurea nigra*	49
Ranunculus acris	175	*Brachypodium sylvaticum*	47
Corylus avellane	170	*Molinia caerulea*	46
Taraxacum	170	*Alopecurus pratensis*	46
Hyacinthoides non-scripta	168	*Torilis japonica*	46
Arum maculatum	160	*Allium ursinum*	45
Ilex aquifolium	159	*Helictotrichon pratense*	45
Achillea millefolium	146	*Clematis vitalba*	45
Arrhenatherum elatius	144	*Oxalis acetosella*	45
Mercurialis perennis	141	*Ulex europaeus*	44
Poa trivialis	140	*Anagallis arvensis*	44
Rubus	137	*Linum catharticum*	43
Cirsium vulgare	136	*Potentilla anserina*	43
Calluna vulgaris	130	*Phyllitis scolopendrium*	42
Silene dioica	125	*Erica cinerea*	42
Fraxinus excelsior	124	*Alliaria petiolata*	42
Agrostis capillaris	121	*Carex pendula*	41
Lonicera periclymenum	121	*Chenopodium album*	41
Rumex obtusifolius	118	*Lamium galeobdolon*	41

Taxon	Plot Count	Taxon	Plot Count
Lotus corniculatus	114	*Primula vulgaris*	41
Bellis perennis	110	*Conopodium majus*	40
Rumex crispus/obtusifolius	110	*Fagus sylvatica*	40
Anthoxanthum odoratum	109	*Veronica montana*	40
Lolium perenne	107	*Ajuga reptans*	40
Epilobium hirsutum	102	*Erica tetralix*	39
Prunella vulgaris	101	*Sonchus oleraceus*	39
Vaccinium myrtillus	100	*Festuca ovina*	39
Festuca rubra	99	*Teucrium scorodonia*	38
Ranunculus bulbosus	98	*Campanula rotundifolia*	38
Hypochaeris radicata	98	*Cirsium acaule*	38
Potentilla erecta	96	*Phleum pratense*	38
Sambucus nigra	91	*Anemone nemorosa*	37
Taraxacum officinale agg.	88	*Impatiens glandulifera*	37
Stellaria graminea	85	*Vicia sepium*	37
Rumex crispus	85	*Calystegia sepium*	37
Stachys sylvatica	85	*Pilosella officinarum*	37
Cirsium palustre	85	*Briza media*	36
Cynosurus cristatus	82	*Cornus sanguinea*	36
Stellaria holostea	82	*Myosotis arvensis*	36
Veronica chamaedrys	82	*Alnus glutinosa*	36
Plantago major	81	*Alopecurus myosuroides*	36
Circaea lutetiana	80	*Tripleurospermum inodorum*	36
Deschampsia flexuosa	77	*Veronica persica*	36
Lathyrus pratensis	76	*Dryopteris filix-mas*	35
Quercus robur	76	*Poa pratensis*	35
Galium saxatile	76	*Potentilla sterilis*	34
Juncus inflexus/effusus/conglomeratus	76	*Sorbus aucuparia*	34
Agrostis stolonifera	74	*Solanum dulcamara*	34
Potentilla reptans	74	*Galium palustre*	34
Filipendula ulmaria	73	*Picris echioides*	34
Stellaria media	73	*Dryopteris dilatata*	34
Juncus effuses	71	*Elytrigia repens*	34
Digitalis purpurea	70	*Juncus squarrosus*	33
Geranium dissectum	66	*Typha latifolia*	33
Vicia cracca	66	*Betula pendula*	33
Acer pseudoplatanus	65	*Eriophorum vaginatum*	32
Rumex	65	*Epilobium montanum*	32
Lamium album	62	*Chaerophyllum temulum*	32
Galium mollugo	62	*Veronica arvensis*	32
Cardamine pratensis	61	*Eriophorum angustifolium*	31
Poa annua	59	*Origanum vulgare*	31
Dioscorea communis	58	*Corylus*	31
Rumex sanguineus	56	*Carex sylvatica*	30
		Phragmites australis	30

Northern Ireland

For Northern Ireland (Table A1.4), the top ten species are reported, given that only one species exceeds the 30-plot cut-off used elsewhere.

Table A1.4. Counts of unique NPMS plots (i.e. spatially unique locations) for taxa in Northern Ireland: The top ten species. Counts correct for 2015/2016 at the time of reporting.

Taxon	Plot Count
Potentilla erecta	40
Holcus lanatus	27
Juncus squarrosus	25
Calluna vulgaris	25
Molinia caerulea	24
Anthoxanthum odoratum	23
Eriophorum angustifolium	21
Juncus inflexus/effusus/conglomeratus	20
Eriophorum vaginatum	19
Erica cinerea	19

Scotland

Table A1.5. Counts of unique NPMS plots (i.e. spatially unique locations) for taxa in Scotland, where greater than 30. Counts correct for 2015/2016 at the time of reporting. Plots were assigned to Scotland on the basis of their parent 1 km square; where 1 km squares overlap country boundaries, the square was assigned to the country accounting for the largest proportion of its area.

Taxon	Plot count	Taxon	Plot count
Potentilla erecta	128	*Lotus corniculatus*	44
Calluna vulgaris	127	*Rubus fruticosus* agg.	44
Ranunculus repens	91	*Cirsium palustre*	43
Holcus lanatus	87	*Narthecium ossifragum*	42
Urtica dioica	82	*Oxalis acetosella*	41
Rumex acetosa	74	*Eriophorum angustifolium*	40
Galium aparine	70	*Carex nigra*	39
Ranunculus acris	69	*Sorbus aucuparia*	38
Anthoxanthum odoratum	68	*Viola riviniana*	38
Trifolium repens	68	*Agrostis capillaris*	37
Vaccinium myrtillus	68	*Heracleum sphondylium*	36
Galium saxatile	67	*Nardus stricta*	35
Cirsium arvense	58	*Juncus squarrosus*	34
Erica tetralix	57	*Cerastium fontanum*	34
Plantago lanceolate	57	*Prunella vulgaris*	34
Juncus effuses	55	*Cardamine pratensis*	32
Erica cinereal	54	*Deschampsia cespitosa*	32
Molinia caerulea	51	*Juncus inflexus/effusus/conglomeratus*	32
Pteridium aquilinum	48	*Carex panicea*	30
Deschampsia flexuosa	48	*Geum urbanum*	30
Succisa pratensis	45	*Vaccinium vitis-idaea*	30
		Senecio jacobaea	30

Wales

Table A1.6. Counts of unique NPMS plots (i.e. spatially unique locations) for taxa in Wales, where greater than 30. Counts correct for 2015/2016 at the time of reporting. Plots were assigned to Wales on the basis of their parent 1 km square; where 1 km squares overlap country boundaries, the square was assigned to the country accounting for the largest proportion of its area.

Taxon	Plot Count	Taxon	Plot Count
Urtica dioica	83	*Heracleum sphondylium*	44
Rubus fruticosus agg.	80	*Hedera helix*	43
Ranunculus repens	72	*Calluna vulgaris*	43
Holcus lanatus	66	*Digitalis purpurea*	41
Potentilla erecta	63	*Galium saxatile*	41
Galium aparine	56	*Cirsium arvense*	41
Pteridium aquilinum	50	*Rumex acetosa*	38
Trifolium repens	50	*Cirsium palustre*	38
Plantago lanceolata	50	*Vaccinium myrtillus*	37
Anthoxanthum odoratum	48	*Ranunculus acris*	36
Crataegus monogyna	44	*Cerastium fontanum*	36
		Anthriscus sylvestris	33

Annex 2: Designing an NPMS indicator: Technical appendix to section 2.5

Introduction

Indicators should be straightforward, and easily interpretable. Here we outline a proposal for a plant species richness indicator derived from plot data collected within the National Plant Monitoring Scheme (NPMS). The framework is flexible and could easily be extended to incorporate plot data collected under other schemes (e.g. the Countryside Survey [CS]).

Proposal

NPMS volunteers record species within small plots (typically 5 x 5 m) across the British countryside. Once their plots are selected (an activity restricted to the first year of a volunteer's engagement with the scheme), the volunteer makes two decisions: which level of habitat discrimination to record at (broad or fine) and which level of expertise to record at (Wildflower, Indicator, and Inventory). The simplest approach to modelling these data, whilst also allowing for the focus on different subsets of species implied by these two decisions, is arguably to model species richness, whilst adjusting for the different recording levels and habitat discrimination (as well as other factors such as habitat type). Such an approach allows for the incorporation of all data and allows for the estimation of the effects of covariates (such as surveyor level) as an integral part of the modelling process. Additional plot data could also be jointly analysed under such a scheme by including additional covariates to account for scheme type (e.g. NPMS versus CS).

Species richness is often modelled using a generalised linear modelling (GLM) framework, using a log-link; that is, a Poisson GLM. Our data may be expected to demonstrate both temporal (after a sufficient number of years of data collection) and spatial autocorrelation, therefore a mixed-effects framework (or hierarchical model) is likely to be most appropriate; within a frequentist framework these types of models are referred to as generalised linear mixed effects models (GLMMs). Note that count data may also exhibit over-dispersion, whereby the variance greatly exceeds the mean; in this case the negative binomial distribution may be a better distribution for the modelling of species richness. It may also be worth considering zero-inflated distributions: the Poisson or negative binomial distributions will be expected to only exhibit a certain number of zeros in their distributions, so-called 'zero-inflated' versions of these distributions can be considered in these circumstances.

Bayesian statistics provide a way of running hierarchical models, allowing for missing data, and accounting for unbalanced and/or small samples (which is likely to be the case for some combinations of habitat and surveyor level); note, however, that this is not a panacea for small samples, small sets of data at certain levels will typically result in higher uncertainty. With the development of Markov Chain Monte Carlo (MCMC) sampling over the past twenty years, Bayesian techniques are now able to handle increasingly large datasets and complex model structures. Spatio-temporal models are readily available within a Bayesian framework and are applied in a range of fields, such as epidemiology and ecology.

MCMC sampling can be computationally expensive and complex models can take days if not weeks for model parameters to converge. However, recent developments in overcoming this issue have led to integrated nested Laplace approximation (INLA), a deterministic algorithm used for Bayesian inference (Rue *et al*. 2009). INLA uses Laplace approximations to produce approximate (marginal) posterior distributions to the normal distribution for parameters (Rue *et al*. 2009; Blangiardo & Cameletti 2015), but as it does not depend on simulations it is much faster than MCMC. INLA can be applied to a wide range of latent

Gaussian models, from generalised linear models to spatio-temporal models (Blangiardo & Cameletti, 2015).

The NPMS data was collated for all species recorded per plot, per monad, across 2015 and 2016. The response was species richness, regardless of whether the plant species is a positive indicator species or not. Year has been fixed such that data from 2015 take the value of zero, and 2016 data takes the value of one.

Models

Two sets of models are considered; frequentist GLMMs and Bayesian models as implemented using INLA. The GLMM models are specified as follows:

$SppRichness_{ij} = Poisson(\lambda_{ij})$
$\lambda_{ij} = \exp(beta0_{j[i]} + (beta1 \times year) + (beta2_{1...K} \times level_k) + (beta3_{1...L} \times habitat_l))$

Where:
i = plot; j = monad; k = surveyor level; l = broad habitat;
$beta0_{j[i]} = beta0 + \gamma_0$;
$\gamma_0 \sim Normal(0, \sigma^2_{beta0})$;
beta1 is the year effect;
beta2 is a vector of surveyor type effects;
beta3 is a vector of broad habitat effects.

Beta0 is the mean intercept across all plots/monads; $beta0_{j[i]}$ is the random intercept per plot nested within monad j; γ_0 is the monad-level variation around this mean intercept; σ^2_{beta0} explains the variance of the monad-level variation.

We consider other distributions for the response below – negative binomial to take account of over dispersion and zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) models.

The Bayesian model, as implemented within INLA, is specified as follows:

$SppRichness_{ij} = Poisson(\lambda_{ij})$
$\lambda_{ij} = \exp(beta0 + (beta1 \times year) + (beta2_{1...K} \times level_k) + (beta3_{1...L} \times habitat_l) + f(SPDE) + f(monad_j))$

Where:
$beta0_{j[i]}$ is the random intercept per plot nested within monad j;
f(SPDE) takes account of the spatial autocorrelation;
$f(monad_j)$ takes account of the nesting of plots within monads (i.e. monad as a nested random effect).

There are also variants of this model, such as treating surveyor type and broad habitat as random effects; these are investigated below.

Results

Table A2.1 indicates that the three levels of surveyors did not survey vastly different proportions of habitats. Table A2.2 indicates an insubstantial increase in surveying in 2016. Figure A2.1 provides the geographical spread of Great Britain monads surveyed, according to the three levels of surveyor, and across all surveys. The geographical spread seems fairly similar across the surveyor types, but there are no wildflower plots in Northern Ireland. Plots of species richness counts by surveyor type (Figure A2.2), broad habitat (Figure A2.3) and year (Figure A2.4) are given. The only level which indicates a much higher or lower species richness count is that done under the Inventory level, which is not surprising, as these surveyors were surveying all species present, per plot i.e. median species richness is 5.0 (Indicator), 15.0 (Inventory) and 4.0 (Wildflower). Note that all analyses and figures exclude the 19 Channel island records and will represent GB alone, NI alone or UK (GB + NI).

Table A2.1. Proportion of habitats surveyed across all plots by three levels of surveyor, across UK.

Habitat	Indicator Survey	Inventory Survey	Wildflower Survey
Arable margins	0.086	0.063	0.078
Bog and wet heath	0.073	0.04	0.038
Broadleaved woodland, hedges and scrub	0.311	0.322	0.355
Coast	0.072	0.068	0.042
Freshwater	0.07	0.071	0.051
Heathland	0.064	0.035	0.071
Lowland grassland	0.255	0.295	0.291
Marsh and fen	0.036	0.05	0.024
Native pinewood and juniper scrub	0.006	0.011	0.014
Rock outcrops, cliffs and scree	0.016	0.019	0.015
Upland grassland	0.01	0.027	0.022

Table A2.2. Proportion of years surveyed across all plots by three levels of surveyor, UK.

Year	Indicator Survey	Inventory Survey	Wildflower Survey
2015	0.491	0.468	0.486
2016	0.509	0.532	0.514

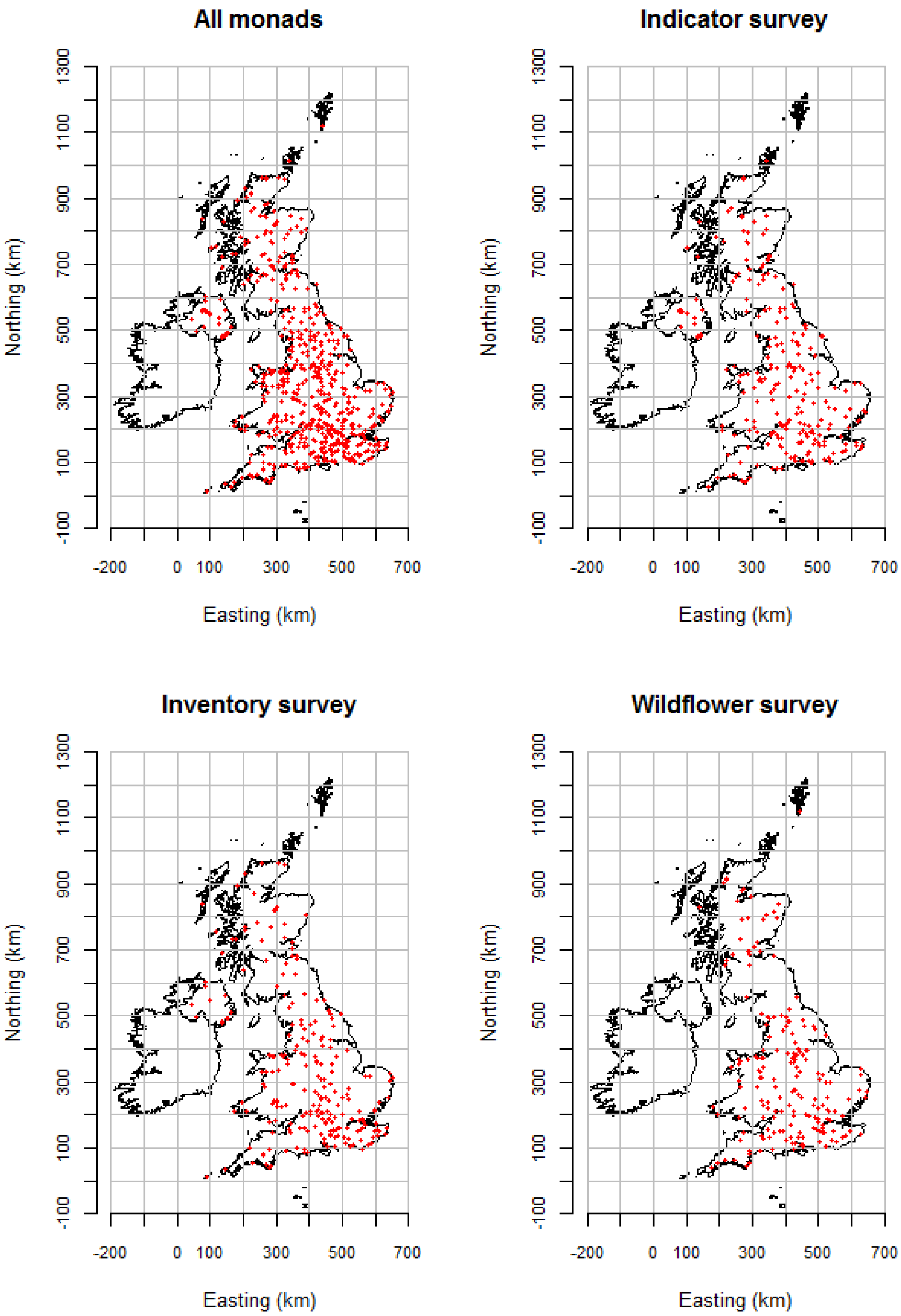

Figure A2.1. Plot of UK monads with at least one plot within a surveyor type: all monads; indicator survey; inventory survey; and wildflower survey.

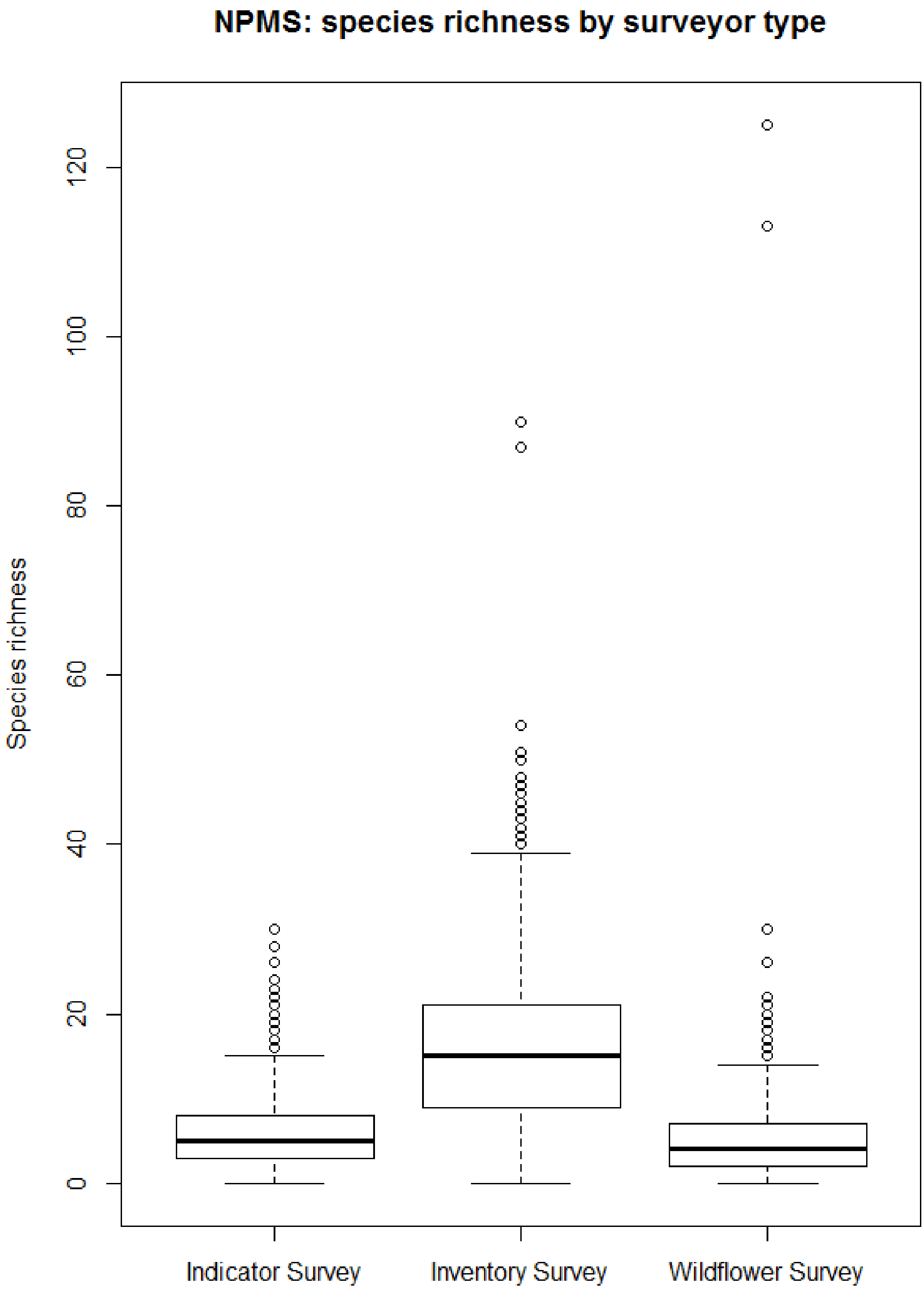

Figure A2.2. Species richness at the plot level, by surveyor type, across UK. The four outliers are from the database and are currently being investigated.

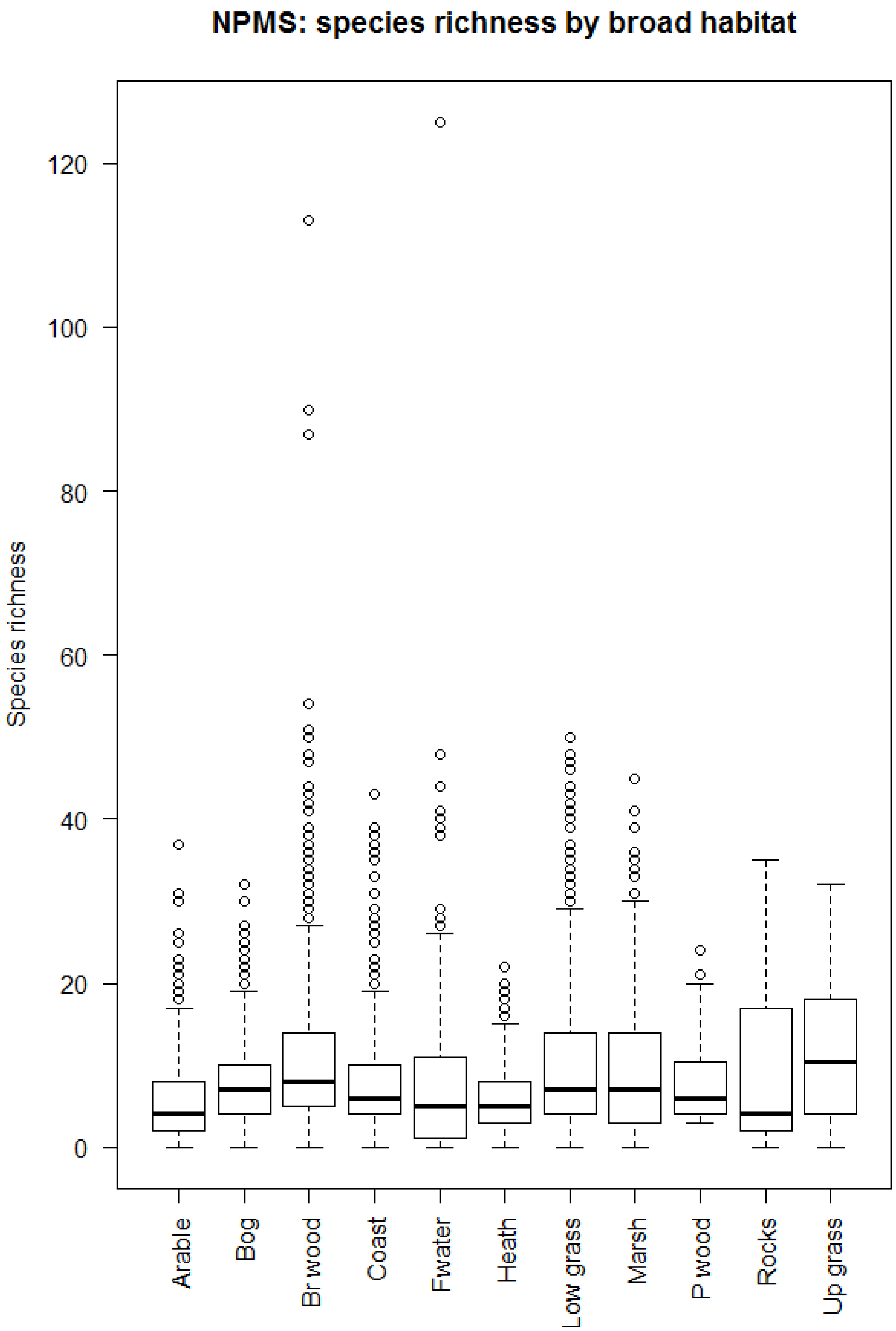

Figure A2.3. Species richness at the plot level, by broad habitat, across UK. The four outliers are from the database and are currently being investigated.

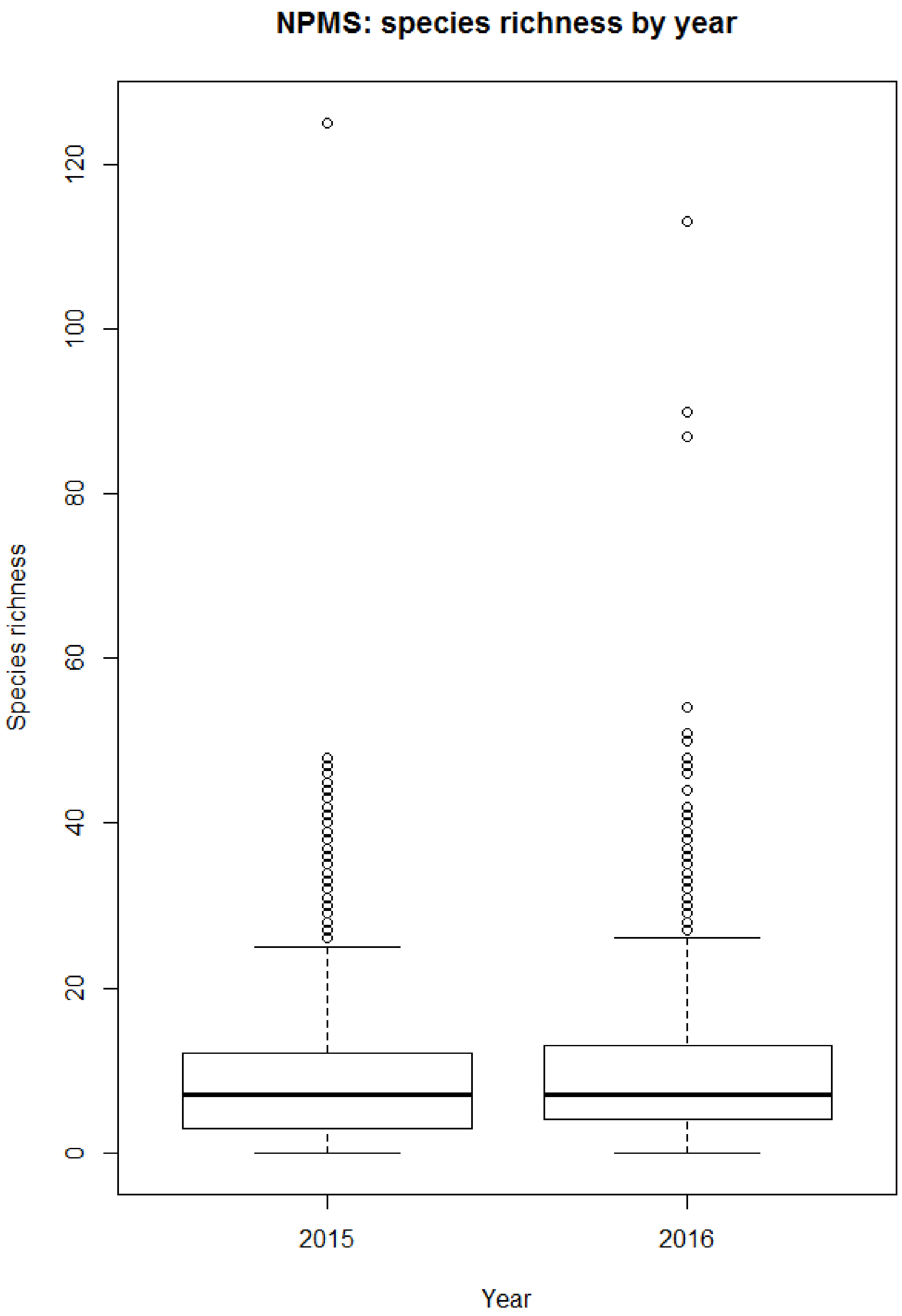

Figure A2.4. Species richness at the plot level, by year, across UK. The four outliers are from the database and are currently being investigated.

The simplest models to run are the series of GLMMs – whereby the counts are described by Poisson, negative binomial, zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) distributions (Table A2.3).

Table A2.3. Effect of year (2016 vs. 2015) and intercept estimate (SD), adjusted for surveyor type and broad habitat, for each of the mixed effects models, across UK.

Error distribution	No. plot samples (no. monads)	Intercept (SD)	Year effect (SD)	AIC	BIC
Poisson	6061 (584)				
model 1		1.692 (0.026)	0.102 (0.010)	38,662.3	38,695.9
model 2		1.345 (0.033)	0.103 (0.010)	37,671.1	37,771.7
Neg Bin	6061 (584)				
model 1		1.678 (0.030)	0.082 (0.017)	34,988.7	35,028.9
model 2		1.316 (0.042)	0.085 (0.016)	34,561.3	34,668.7
ZIP	6061 (584)				
model 1		1.762 (0.026)	0.083 (0.011)	36,819	
model 2		1.452 (0.034)	0.083 (0.011)	35,971.4	
ZINB	6061 (584)				
model 1		1.712 (0.029)	0.082 (0.016)	34,641	
model 2		1.386 (0.042)	0.085 (0.016)	34,211.2	

Note that model 1 adjusts for just surveyor type, whereas model 2 adjusts for both surveyor type and broad habitat. There are convergence issues with the non-zero inflated models with broad habitat included, so it may be best to focus on the models without broad habitat as a fixed effect.

Amongst the models without broad habitat included, the over-dispersion parameter in the negative binomial model is 5.861 and for the ZINB model is 7.551. No matter which distribution is chosen, the mean count in 2015 is approximately exp(1.7) and in 2016 is approximately exp(1.7 + 0.08), equating to means of 5.5 and 5.9, respectively.

A series of INLA models have been run to model the effects of year, surveyor type, broad habitat, whilst taking account of the dependence of data within monads and the SPDE. All models include an intercept and year as a fixed effect and the SPDE as a random effect to take account of the spatial autocorrelation. Additional covariates may include surveyor type (dummy variables) and broad habitat (dummy variable), whereas monad, surveyor type and broad habitat can also be considered as random effects. The models are thus described as:

Model 3.1: INTERCEPT + YEAR + TYPE (DUMMY) + F(MONAD) + F(SPDE) + F(HABITAT)
Model 3.2: INTERCEPT + YEAR + F(MONAD) + F(SPDE) + F(HABITAT)
Model 3.3: INTERCEPT + YEAR + TYPE (DUMMY) + F(SPDE) + F(HABITAT)
Model 3.4: INTERCEPT + YEAR + TYPE (DUMMY) + HABITAT (DUMMY) + F(MONAD) + F(SPDE)
Model 3.5: INTERCEPT + YEAR + HABITAT (DUMMY) + F(MONAD) + F(SPDE)
Model 3.6: INTERCEPT + YEAR + TYPE (DUMMY) + HABITAT (DUMMY) + F(SPDE)
Model 3.7: INTERCEPT + YEAR + F(SPDE) + F(MONAD) + F(HABITAT) + F(TYPE)
Model 3.8: INTERCEPT + YEAR + F(SPDE) + F(HABITAT) + F(TYPE)
Model 3.9: INTERCEPT + YEAR + HABITAT (DUMMY) + F(SPDE) + F(MONAD) + F(TYPE)
Model 3.10: INTERCEPT + YEAR + HABITAT (DUMMY) + F(SPDE) + F(TYPE)

The parameter estimates for the Intercept and year are given in Table 3.

Table A2.4. Effect of year (2016 vs. 2015) and intercept estimate for each of the models, across GB.

Model	Intercept – median (2.5th, 97.5th centiles)	Year effect – median (2.5th, 97.5th centiles)	Max. 97.5th centile [1]	DIC
Model 3.1	1.611 (-5.974, 9.114)	0.099 (0.078, 0.119)	9.114 (intercept)	35,687.46
Model 3.2	1.839 (1.721, 1.960)	0.113 (0.093, 0.134)	1.960 (intercept)	36,037.88
Model 3.3	1.586 (1.459, 1.712)	0.087 (0.067, 0.106)	1.712 (intercept)	37,140.42
Model 3.4	1.377 (-5.360, 8.074)	0.099 (0.079, 0.119)	8.074 (intercept)	35,687.20
Model 3.5	1.599 (1.513, 1.691)	0.113 (0.093, 0.134)	1.691 (intercept)	36,038.81
Model 3.6	1.352 (1.255, 1.448)	0.087 (0.067, 0.106)	1.448 (intercept)	37,139.63
Model 3.7	1.814 (-7.135, 10.547)	0.099 (0.079, 0.119)	10.547 (intercept)	35,685.96
Model 3.8	1.847 (1.254, 2.440)	0.087 (0.067, 0.106)	2.440 (intercept)	37,140.27
Model 3.9	1.583 (-7.157, 10.181)	0.099 (0.079, 0.120)	10.181 (intercept)	35,686.23
Model 3.10	1.613 (1.036, 2.189)	0.087 (0.067, 0.106)	2.189 (intercept)	37,140.53

[1] Maximum upper credible interval across all other fixed effects terms – including intercept and year for all models; type as two dummy variables; and broad habitat as ten dummy variables.

We can see that 4/10 models have parameter estimates that have extremely high upper credible intervals for the intercept (noting that an upper value of 10 is on the log scale and so refers to a species richness of 22,000, whereas the actual data had a maximum species richness of 125). All four of these models contain both surveyor type (fixed or random) and monad. The remaining six models do not contain both terms and give both plausible parameter estimates and the geographical banding seen in Figures A2.5, A2.8, A2.11 and A2.13 are not present.

For models 3.2 and 3.5, which contain monad and not surveyor type, the distribution of the random field, the spatial approximation of the response, indicate the geographical hotspots being in western Scotland, Wales, South West England and the South East (Figures A2.6 and A2.9). The variance is largely constant across this spatial surface. Conversely, models 3.3, 3.6, 3.8 and 3.10, which contain surveyor type and not monad, have largely constant mean species richness (Figures A2.7, A2.10, A2.12 and A2.14), whereas the variance is higher in many of those areas that models 3.2 and 3.5 indicate higher species richness. Ecologically it makes more sense to include surveyor type in the models, rather than monad. So, if we wish to have an overall indicator model, then treating surveyor type and broad habitat as random effects (Model 3.8) is the most applicable model. If we wish to produce separate indicators for surveyor type and habitat, then treating these two factors as fixed effects (Model 3.6) is currently the most appropriate model. For both models (two of the worst fitting models of the ten), the year effect is very similar i.e. for Model 3.8 the median species richness in 2015, after accounting for the spatial autocorrelation and the dependence in species richness across plots with the same surveyor type and broad habitat, is $\exp(1.847) = 6.341$, (95% CrI: 3.504, 11.476) and in 2016 the median species richness is $\exp(1.847 + 0.087) = 6.916$, (95% CrI: 3.748, 12.761).

The findings from these models suggest that controlling for the spatial field, the nesting by monad and surveyor type is over fitting the model. Fitting a model with all three terms results in some very uncertain parameter estimates (omitting the spatial field effectively results in a GLMM), which appears to be partially responsible for the geographic banding in the distribution maps. It is hoped that with additional years of data, the extremely wide credible intervals for the intercept and the geographic banding that we see in models 3.1, 3.4, 3.7 and 3.9 will diminish. We will therefore consider models which exclude monad effects and that treat both surveyor type and broad habitat as either fixed effects (Model 3.6) or as random effects (model 3.8) as the most promising of the ten models.

Having tested the ten various models, we next apply models 3.6 and 3.8 to United Kingdom (models 3.6b and 3.8b; Table A2.4; Figures A2.15 and A2.16). I.e. for Model 3.8b the median species richness in 2015, after accounting for the spatial autocorrelation and the dependence in species richness across plots with the same surveyor type and broad habitat, is exp(1.876) = 6.527, (95% CrI: 3.663 – 11.619) and in 2016 the median species richness is exp(1.876 + 0.070) = 6.999, (95% CrI: 3.855 – 12.692); Figure A2.17.

Model 3.8b (and Model 3.8) can be formulated as:

$$\text{SppRichness}_{ij} = \text{beta0} + (\text{beta1 x year}) + \text{f(level)} + \text{f(habitat)} + \text{f(SPDE)} + \varepsilon_{i,j}$$

Table A2.4. Effect of year (2016 vs. 2015) and intercept estimate for each of the models, across UK.

Model	Intercept – median (2.5th, 97.5th centiles)	Year effect – median (2.5th, 97.5th centiles)	Max. 97.5th centile [1]	DIC
Model 3.6b	1.397 (1.307, 1.487)	0.071 (0.052, 0.089)	1.487 (intercept)	38,844.86
Model 3.8b	1.876 (1.298, 2.453)	0.070 (0.051, 0.088)	2.453 (intercept)	38,774.40

Note that when three extra years of data is bootstrapped from the 2015 and 2016 data at the plot level (each plot with an equal probability of being selected, and with replacement), when the monad random effect is added back to models 3.6b and 3.8b, then the wide credible intervals and geographical banding persists. When the bootstrapped data is for a total of ten years (i.e. eight bootstrapped years of data), then the credible intervals for intercept are narrower (compared to five years of data), but the geographical banding persists (regardless of whether year is treated as a continuous or categorical factor). This indicates that models containing spatial autocorrelation, monad and surveyor type, even with ten years of data, produce uncertain parameter estimates for species richness across years. No explicit results or figures are given for these bootstrapped data.

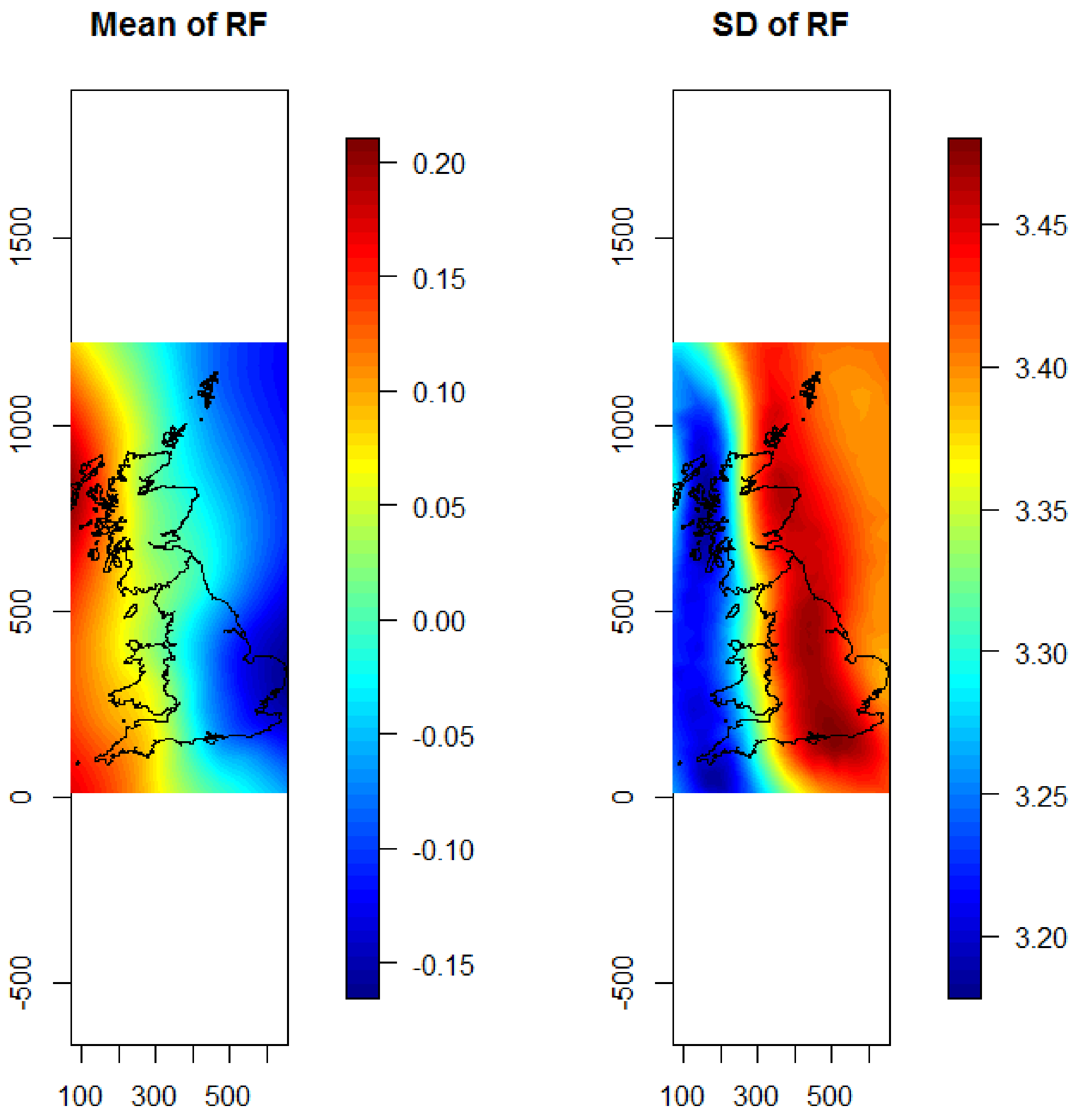

Figure A2.5. Random field for Model 3.1.

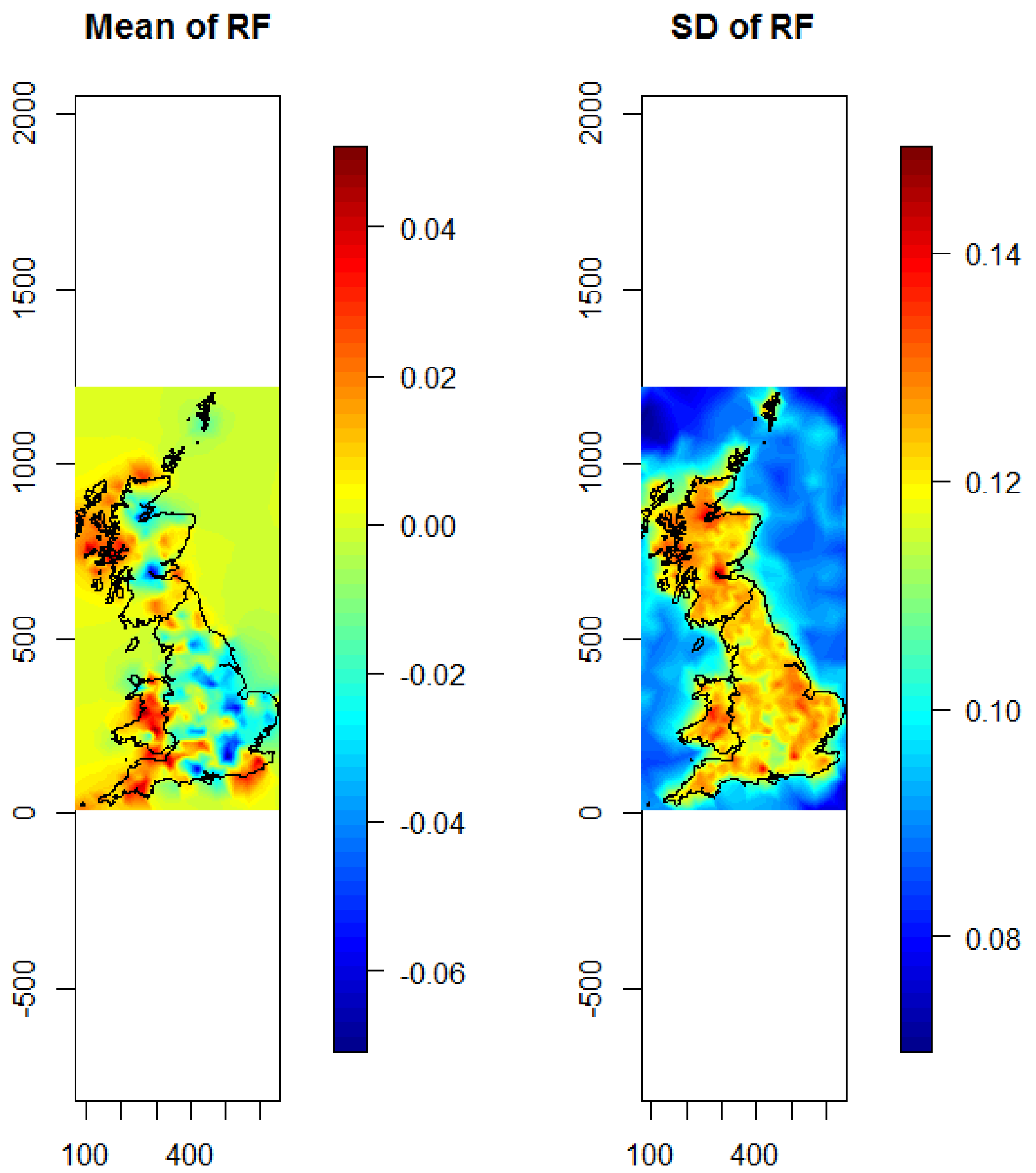

Figure A2.6. Random field for Model 3.2.

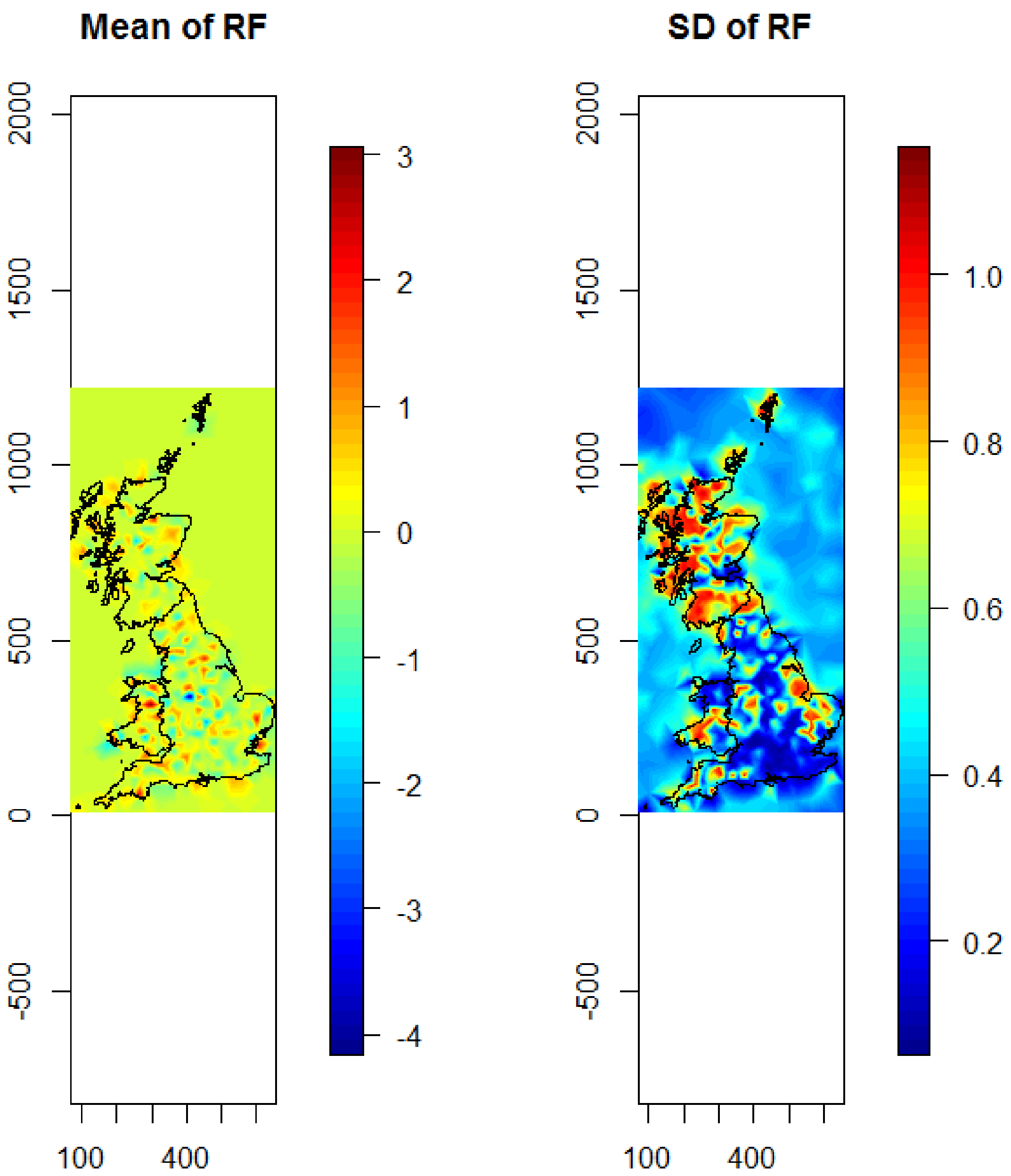

Figure A2.7. Random field for Model 3.3.

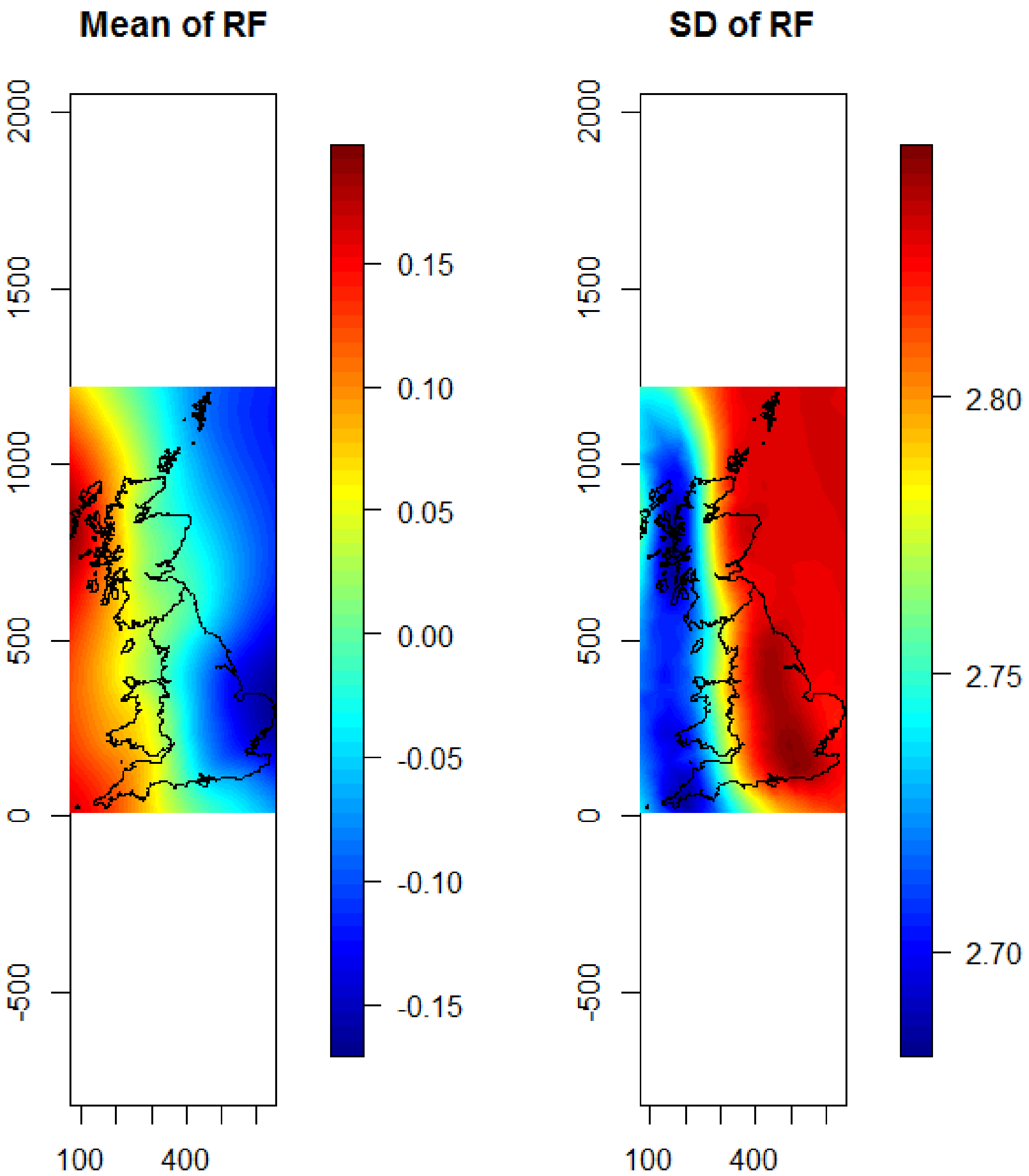

Figure A2.8. Random field for Model 3.4.

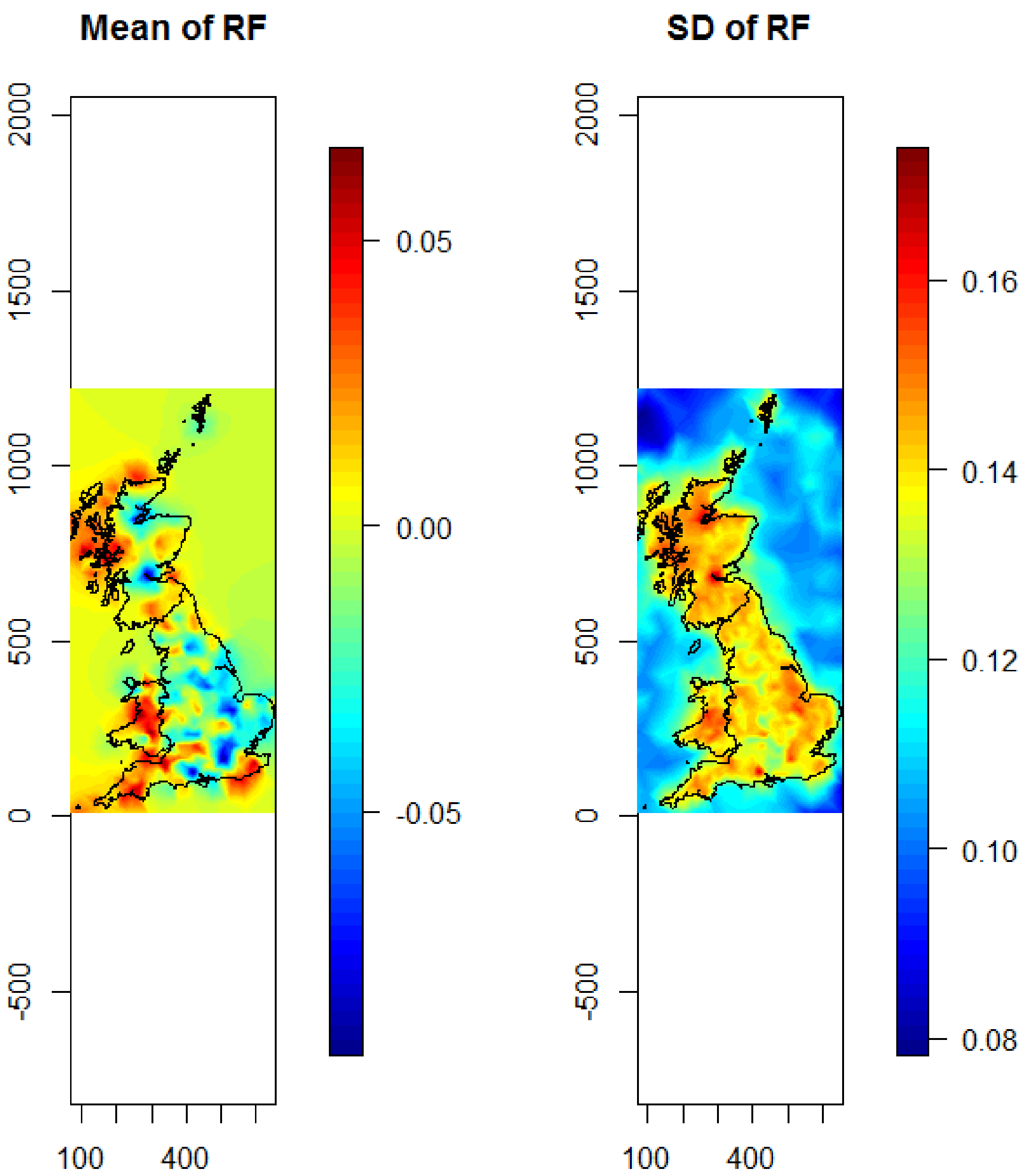

Figure A2.9. Random field for Model 3.5.

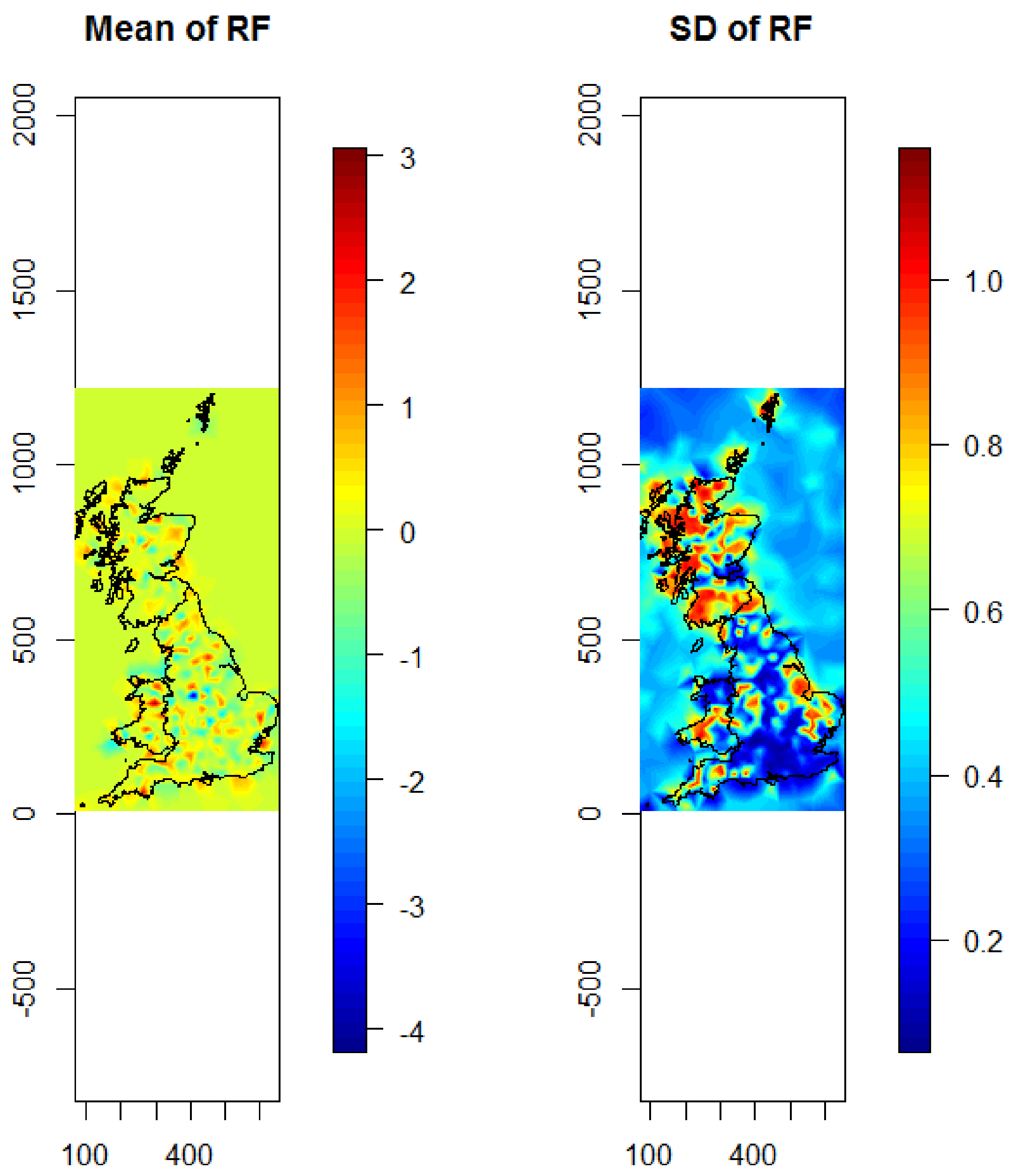

Figure A2.10. Random field for Model 3.6.

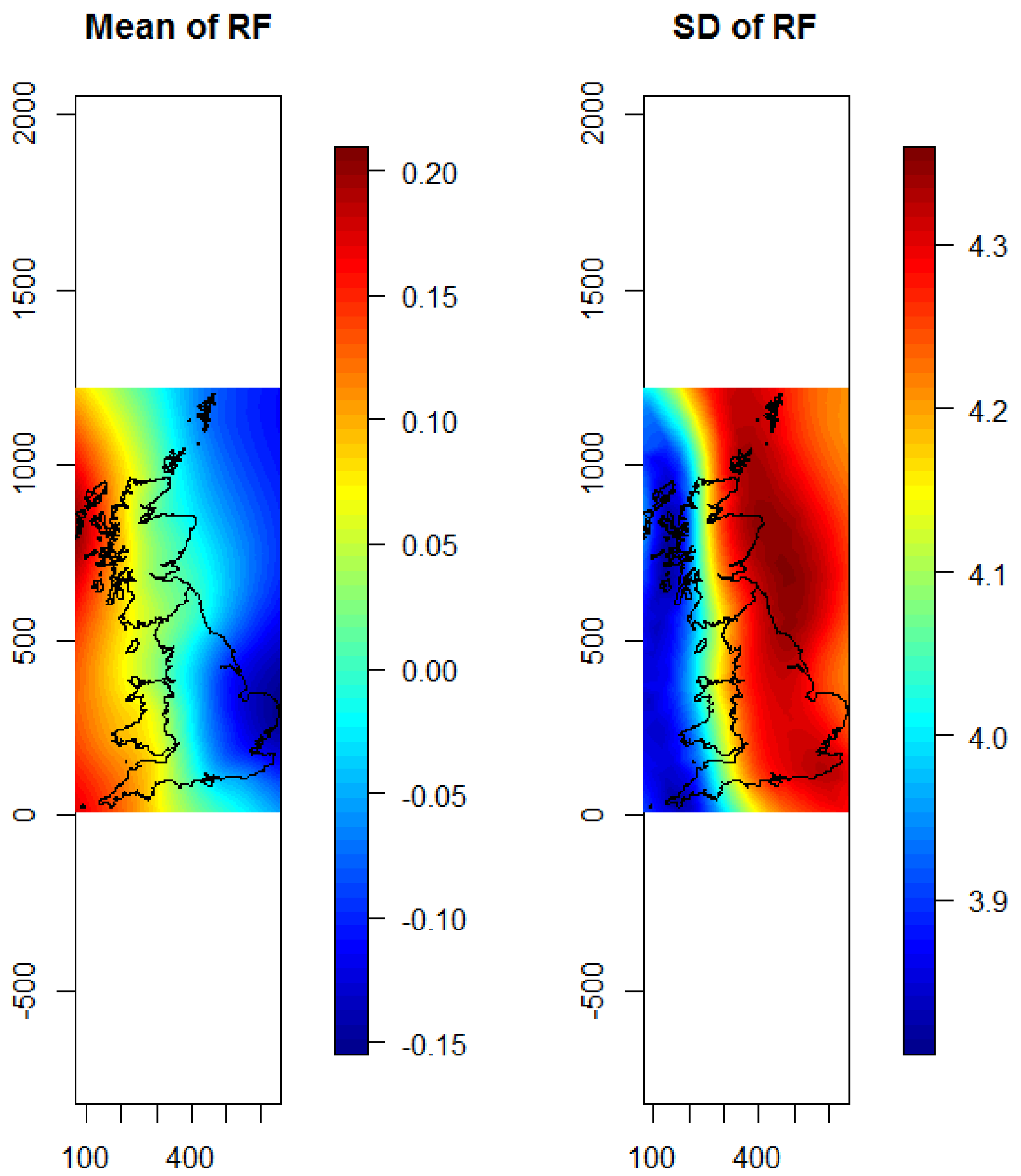

Figure A2.11. Random field for Model 3.7.

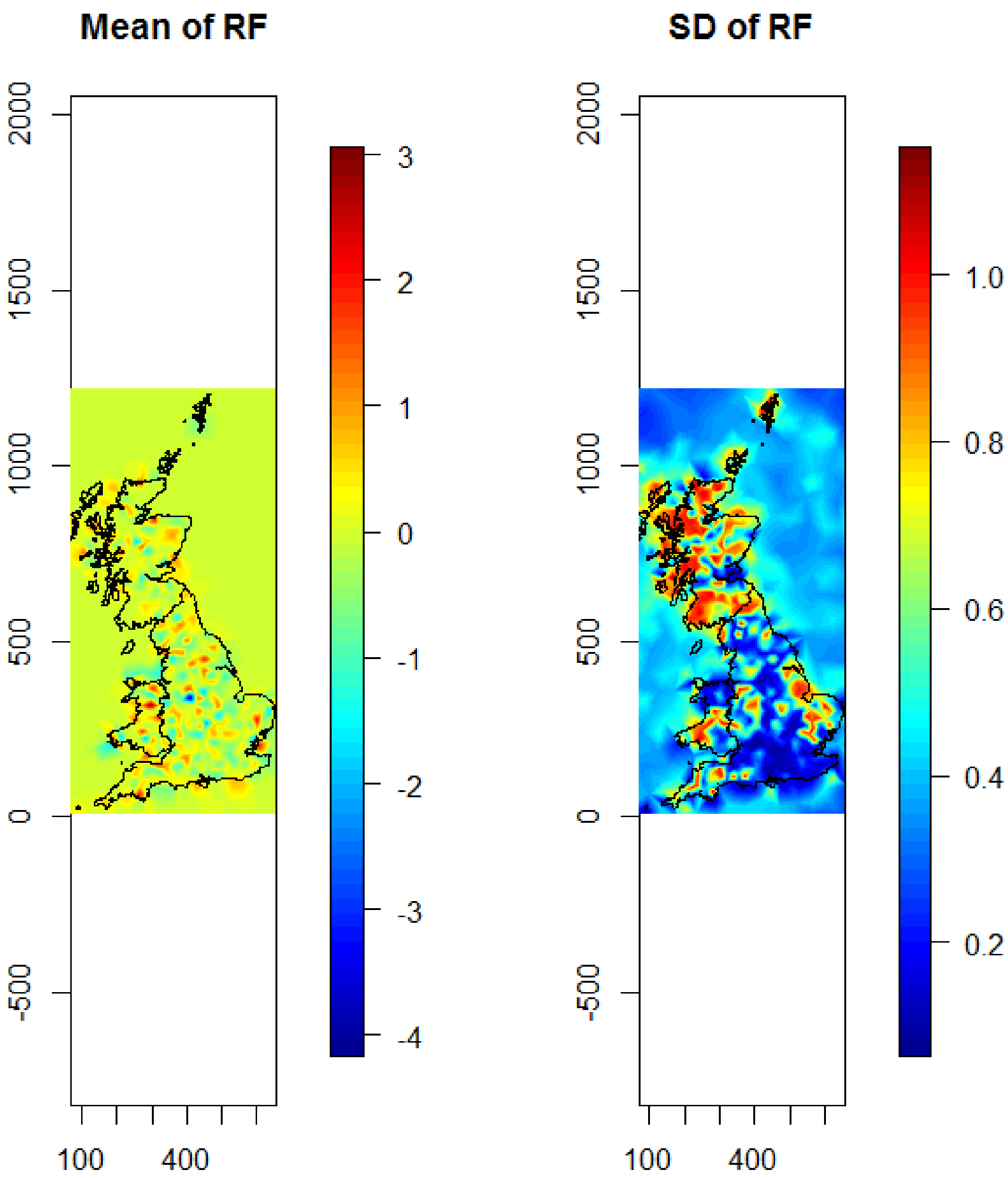

Figure A2.12. Random field for Model 3.8.

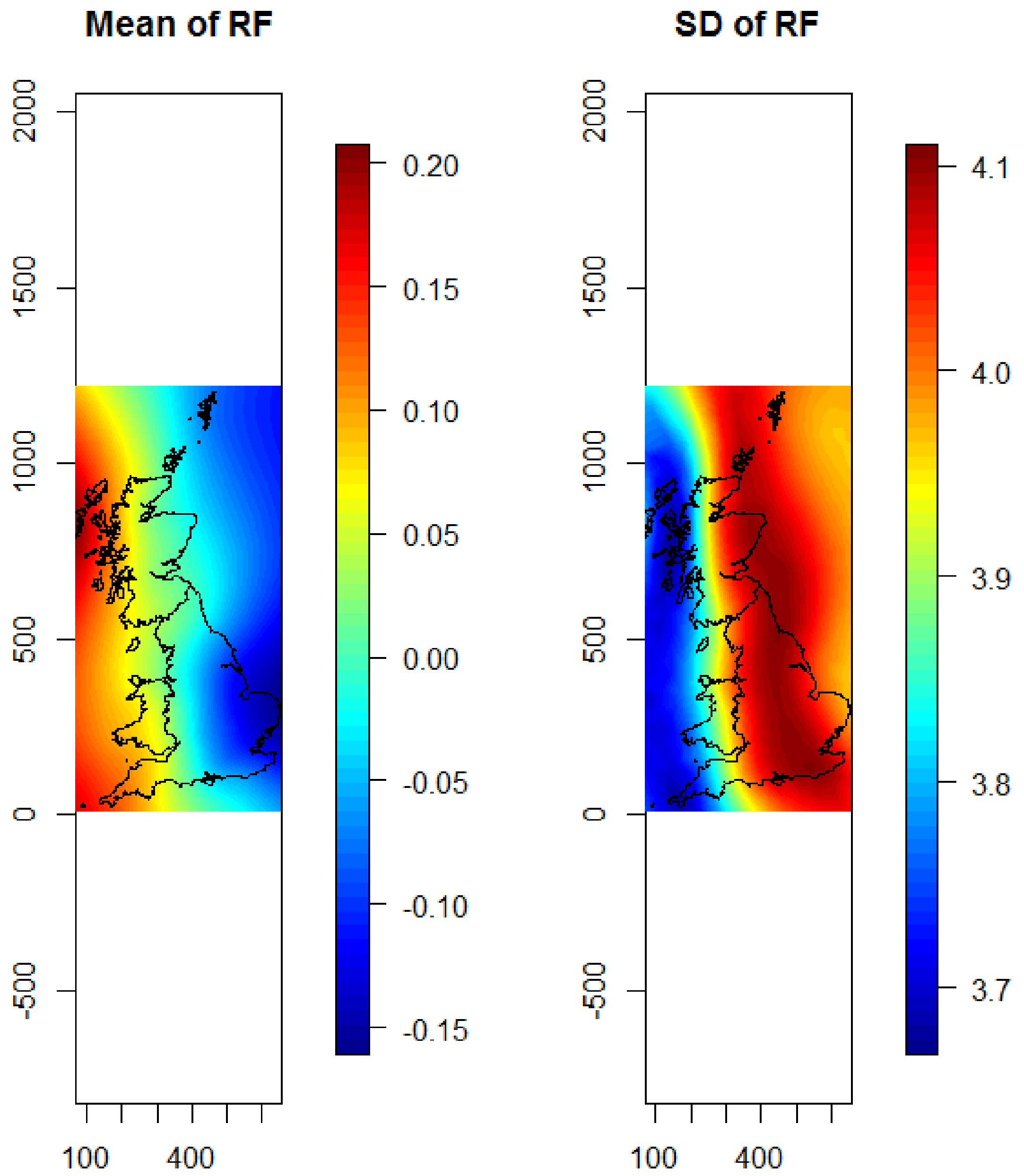

Figure A2.13. Random field for Model 3.9.

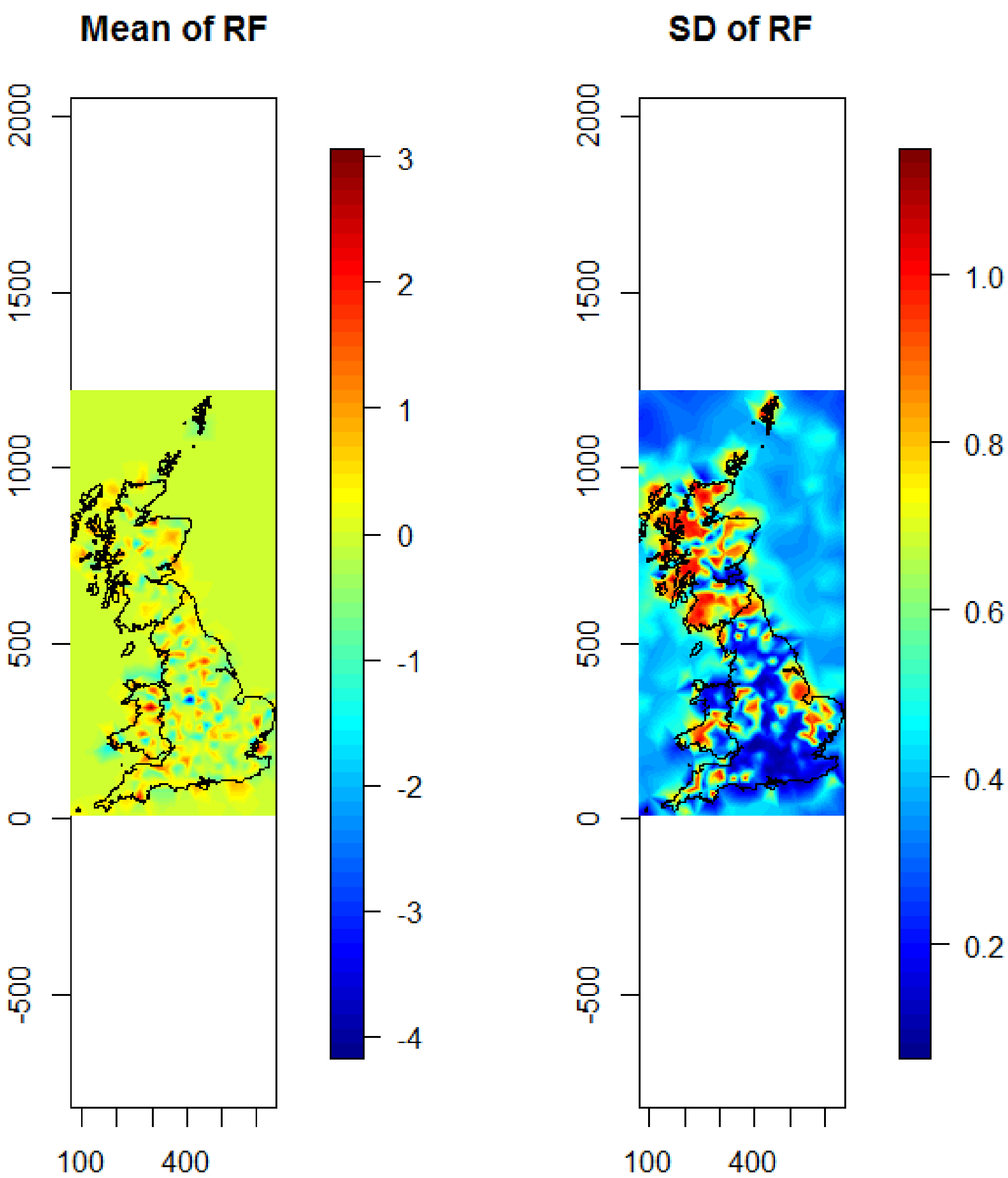

Figure A2.14. Random field for Model 3.10.

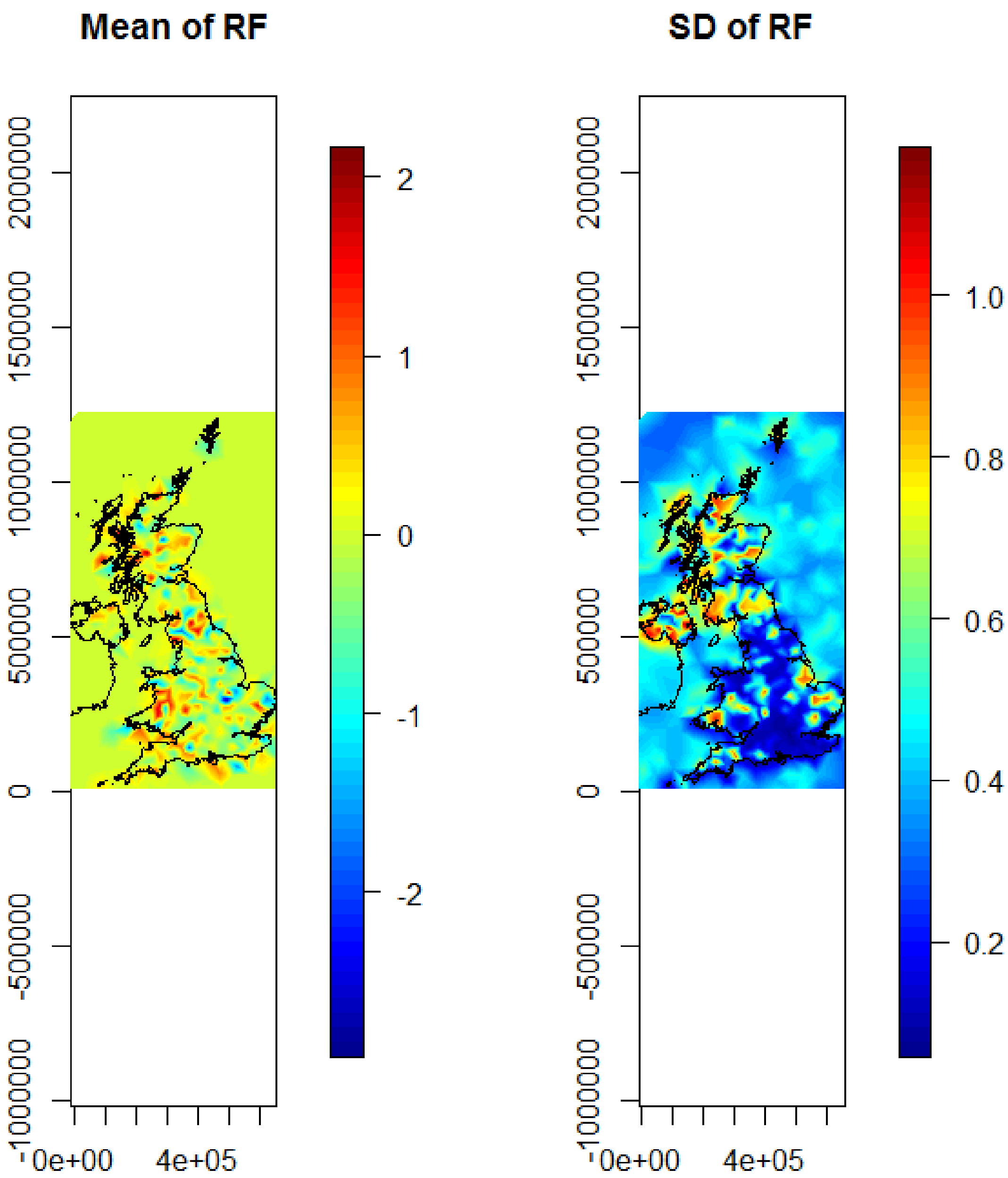

Figure A2.15. Random field for Model 3.6b.

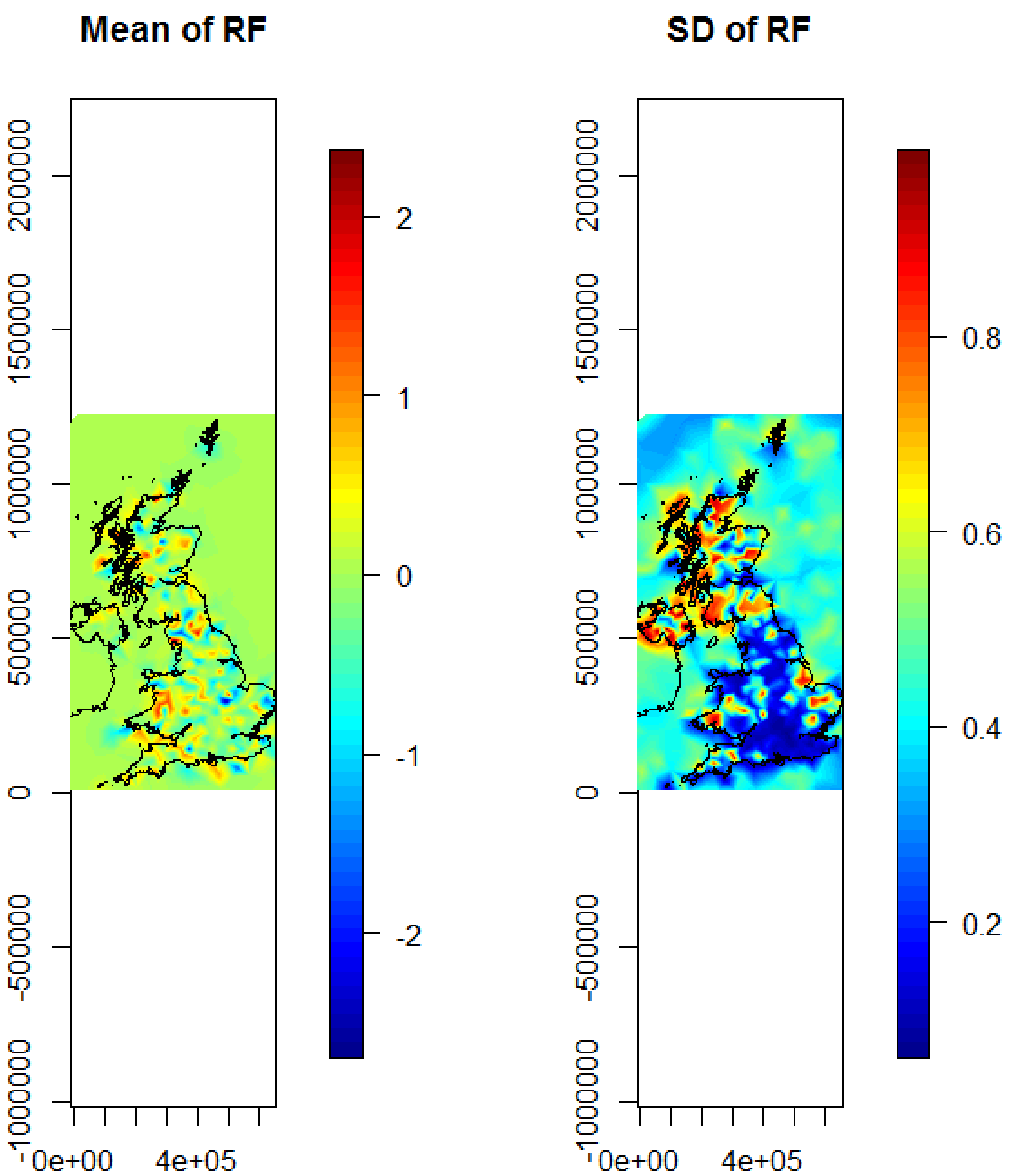

Figure A2.16. Random field for Model 3.8b.

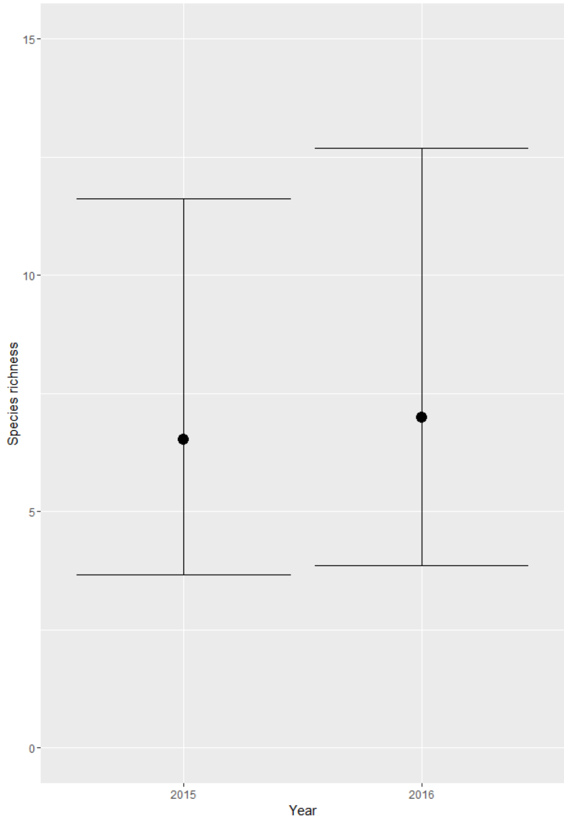

Figure A2.17. Estimated median species richness in 2015 and 2016, across UK, as given by Model 3.8b i.e. year as fixed effect, taking account of between-monad spatial autocorrelation and the dependence within surveyor type levels and within broad habitat levels.

Discussion

The current models assess species richness across all species, regardless of whether the plants are indicator species or not. Future modelling could deal with species richness amongst the positive indicator species only. Also note that the current models are not set up to take account of temporal autocorrelation. This will be more meaningful when we have more than two years of data, and it is possible to implement both forms of autocorrelation (spatial and temporal) within INLA.

In order to obtain habitat-specific or surveyor type-specific parameter estimates within the current modelling framework we may need to run models with these variables included in their respective model as fixed effects (e.g. see section 2.5 in the main report).

Annex 3: Land Cover Map 2015 to NPMS habitat correspondence table

Note that the following table was established on the basis of the descriptions of the Land Cover Map 2015 types given in the LCM 2015 guidance (Centre for Ecology & Hydrology 2017) and on the descriptions of the NPMS habitats given in the Surveyor Guidance document.[6]

[6] https://www.npms.org.uk/sites/default/files/PDF/NPMS_Survey%20Guidance%20notes_WEB_2ndEd.pdf

Aggregate class	Aggregate class number	Broad Habitat	LCM2015 target class	LCM2015	NPMS Habitat	NPMS Habitat Level	Comment
Broadleaf woodland	1	Broadleaved, Mixed and Yew Woodland	Broadleaved woodland	1	Dry deciduous woodland	Fine	
Broadleaf woodland	1	Broadleaved, Mixed and Yew Woodland	Broadleaved woodland	1	Hedgerows of native species	Fine	
Broadleaf woodland	1	Broadleaved, Mixed and Yew Woodland	Broadleaved woodland	1	Wet woodland	Fine	
Coniferous woodland	2	Coniferous Woodland	Coniferous Woodland	2	Native conifer woods and juniper scrub	Fine	
Arable	3	Arable and Horticulture	Arable and Horticulture	3	Arable field margins	Fine	
Improved grassland	4	Improved Grassland	Improved Grassland	4	NA	NA	
Semi-natural grassland	5	Neutral Grassland	Neutral Grassland	5	Neutral pastures and meadows	Fine	
Semi-natural grassland	5	Neutral Grassland	Neutral Grassland	5	Neutral damp grassland	Fine	
Semi-natural grassland	5	Calcareous Grassland	Calcareous Grassland	6	Dry calcareous grassland	Fine	
Semi-natural grassland	5	Calcareous Grassland	Calcareous Grassland	6	Montane calcareous grassland	Fine	
Semi-natural grassland	5	Acid Grassland	Acid Grassland	7	Dry acid grassland	Fine	
Semi-natural grassland	5	Acid Grassland	Acid Grassland	7	Montane acid grassland	Fine	
Semi-natural grassland	5	Fen, Marsh and Swamp	Fen, Marsh and Swamp	8	Acid fens, mires and springs	Fine	
Semi-natural grassland	5	Fen, Marsh and Swamp	Fen, Marsh and Swamp	8	Base-rich fens, mires and springs	Fine	
Mountain, heath, bog	6	Dwarf Shrub Heath	Heather	9	Dry heathland	Fine	
Mountain, heath, bog	6	Dwarf Shrub Heath	Heather grassland	10	Dry heathland	Fine	
Mountain, heath, bog	6	Dwarf Shrub Heath	Heather	9	Montane dry heathland	Fine	
Mountain, heath, bog	6	Bog	Bog	11	Blanket bog	Fine	
Mountain, heath, bog	6	Bog	Bog	11	Raised bog	Fine	
Mountain, heath, bog	6	Bog	Bog	11	Wet heath	Fine	
Mountain, heath, bog	6	Inland Rock	Inland Rock	12	Inland rocks and scree	Fine	
Mountain, heath, bog	6	Inland Rock	Inland Rock	12	Montane rocks and scree	Fine	
Saltwater	7	Saltwater	Saltwater	13	NA	NA	
Freshwater	8	Freshwater	Freshwater	14	Rivers and streams	Fine	
Freshwater	8	Freshwater	Freshwater	14	Nutrient-poor lakes and ponds	Fine	
Freshwater	8	Freshwater	Freshwater	14	Nutrient-rich lakes and ponds	Fine	
Coastal	9	Supra-littoral Rock	Supra-littoral Rock	15	Maritime cliffs and slopes	Fine	Poor equivalence
Coastal	9	Supra-littoral Sediment	Supra-littoral Sediment	16	Coastal sand dunes	Fine	
Coastal	9	Supra-littoral Sediment	Supra-littoral Sediment	16	Coastal vegetated shingle	Fine	
Coastal	9	Supra-littoral Sediment	Supra-littoral Sediment	16	Machair	Fine	
Coastal	9	Littoral Rock	Littoral Rock	17	NA	NA	
Coastal	9	Littoral Sediment	Littoral sediment	18	NA	NA	
Coastal	9	Littoral Sediment	Saltmarsh	19	Coastal saltmarsh	Fine	
Built-up areas and gardens	10	Built-up Areas and Gardens	Urban	20	NA	NA	
Built-up areas and gardens	10	Built-up Areas and Gardens	Suburban	21	NA	NA	
Broadleaf woodland	1	Broadleaved, Mixed and Yew Woodland	Broadleaved woodland	1	Broadleaved woodland, hedges and scrub	Broad	
Coniferous woodland	2	Coniferous Woodland	Coniferous Woodland	2	Native pinewood and juniper scrub	Broad	
Arable	3	Arable and Horticulture	Arable and Horticulture	3	Arable margins	Broad	
Semi-natural grassland	5	Neutral Grassland	Neutral Grassland	5	Lowland grassland	Broad	
Semi-natural grassland	5	Calcareous Grassland	Calcareous Grassland	6	Lowland grassland	Broad	
Semi-natural grassland	5	Acid Grassland	Acid Grassland	7	Lowland grassland	Broad	
Semi-natural grassland	5	Fen, Marsh and Swamp	Fen, Marsh and Swamp	8	Lowland grassland	Broad	
Semi-natural grassland	5	Calcareous Grassland	Calcareous Grassland	6	Upland grassland	Broad	
Semi-natural grassland	5	Acid Grassland	Acid Grassland	7	Upland grassland	Broad	
Semi-natural grassland	5	Fen, Marsh and Swamp	Fen, Marsh and Swamp	8	Marsh and fen	Broad	
Mountain, heath, bog	6	Dwarf Shrub Heath	Heather grassland	10	Heathland	Broad	
Mountain, heath, bog	6	Dwarf Shrub Heath	Heather	9	Heathland	Broad	
Mountain, heath, bog	6	Bog	Bog	11	Bog and wet heath	Broad	
Mountain, heath, bog	6	Inland Rock	Inland Rock	12	Rock outcrops, cliffs and scree	Broad	
Freshwater	8	Freshwater	Freshwater	14	Freshwater	Broad	
Coastal	9	Supra-littoral Rock	Supra-littoral Rock	15	Coast	Broad	
Coastal	9	Supra-littoral Sediment	Supra-littoral Sediment	16	Coast	Broad	
Coastal	9	Littoral Rock	Littoral Rock	17	Coast	Broad	
Coastal	9	Littoral Sediment	Littoral sediment	18	Coast	Broad	
Coastal	9	Littoral Sediment	Saltmarsh	19	Coast	Broad	