Assessing potential data sources for landscape-scale terrestrial biodiversity indicators

Tom Bradfer-Lawrence. RSPB Centre for Conservation Science, Edinburgh, UK, (0000-0001-6045-4360) Corresponding author: tom.bradferlawrence@rspb.org.uk

Meriel Harrison, RSPB, The Lodge, Sandy, UK

Adham Ashton-Butt, British Trust for Ornithology, The Nunnery, Thetford, IP242PU, UK (0000-0002-6926-6099)

Sophie Bennett, British Trust for Ornithology, Stirling, Scotland, UK (0000-0002-7351-5051)

Robin J. Boyd, UK Centre for Ecology and Hydrology, Benson Lane, Crowmarsh Gifford, Wallingford, Oxfordshire, OX10 8BB, UK (0000-0002-7973-9865)

Ella Browning, Leverhulme Centre for Nature Recovery, School of Geography and the Environment, University of Oxford, UK (0000-0002-7959-9292)

Graeme Buchanan, RSPB Centre for Conservation Science, Edinburgh, UK, (0000-0001-9497-8584)

Adam Fraser, Cairngorms National Park Authority, 14 The Square, Grantown-on-Spey, PH23 3HG, UK (0009-0003-6914-6809)

Sian E. Green, Centre for Agroecology Water & Resilience, Wolston Lane, Ryton-on-Dunsmore, Coventry, CV8 3LG, UK (0000-0003-0513-8490)

Robert Hawkes, RSPB Centre for Conservation Science, The Lodge, Sandy, UK (0000-0001-6754-6794)

Becky E. Heath - Department of Zoology, University of Cambridge AND King's College, University of Cambridge, UK (0000-0002-9111-6994)

Pen-Yuan Hsing – Faculty of Health and Life Sciences, University of Bristol, United Kingdom (0000-0002-5394-879X)

Nick J.B. Isaac UK Centre for Ecology and Hydrology, Benson Lane, Crowmarsh Gifford, Wallingford, Oxfordshire, OX10 8BB, UK (0000-0002-4869-8052)

Matthew Jordan, University of the West of England, Bristol, UK (0000-0002-6623-5422)

Francesca Mancini, UK Centre for Ecology & Hydrology, Benson Lane, Crowmarsh Gifford, Wallingford, OX10 8BB, UK (0000-0003-4085-4978)

Oliver Metcalf, Lancaster Environment Centre, Lancaster University, UK. (0000-0003-3441-2591)

David T. Milodowski – School of GeoSciences, University of Edinburgh, UK. (0000-0002-8419-8506)

David O'Brien, NatureScot, Great Glen House, Leachkin Road, Inverness, UK AND Royal Botanic Garden Edinburgh, 20a Inverleith Row, Edinburgh, UK. (0000-0001-7901-295X)

Rory O'Connor, Natural England, Red Kite House, Howbery Park, Crowmarsh Gifford, Wallingford, Oxfordshire, OX10 8BD (0000-0001-7633-4304).

Oliver L. Pescott, UK Centre for Ecology and Hydrology, Benson Lane, Crowmarsh Gifford, OX10 8BB, Oxfordshire, UK (0000-0002-0685-8046)

Jake M. Robinson, College of Science and Engineering, Flinders University, Bedford Park, South Australia, 5042 (0000-0001-8108-3271)

Clare Rowland, UK Centre for Ecology & Hydrology, Library Avenue, Bailrigg, Lancaster, LA1 4AP, UK (0000-0002-0459-506X)

Sarab S. Sethi – Department of Life Sciences, Imperial College London, London, W12 0BZ, UK (0000-0002-5939-0432)

Mike P. Shewring, RSPB Centre for Conservation Science, The Lodge, Sandy, (0000-0001-9272-1611)

Lin Wang, School of Electronic Engineering and Computer Science, Queen Mary University of London, UK (0000-0001-8095-9518)

Oliver R. Wearn, Fauna & Flora, Cambridge, UK (0000-0001-8258-3534)

David E. Wembridge, People's Trust for Endangered Species, 3 Cloisters House, 8 Battersea Park Road, London, SW8 4BG, UK (0009-0008-4246-5937)

Serge A. Wich, School of Biological and Environmental Sciences, Liverpool John Moores University, Liverpool, UK (0000-0003-3954-5174)

Paul Woodcock, Joint Nature Conservation Committee, Quay House, 2 East Station Road, Fletton Quays, Peterborough, PE2 8YY (0000-0002-2178-5447)

Richard D. Gregory. 1. RSPB Centre for Conservation Science, The Lodge, Sandy, UK; 2. Centre for Biodiversity & Environment Research, Department of Genetics, Evolution and Environment, University College London, London, UK

Fiona Burns. RSPB Centre for Conservation Science, The Lodge, Sandy, UK (0000-0002-5362-5552)

Abstract

Global efforts to mitigate anthropogenic pressures on biodiversity and ecosystems will often be realised through management at landscape-scales (i.e., in the range of 100s-1000s km^2). In consequence, we need to measure biodiversity responses at landscape-scales to ensure mitigations are effectively protecting and restoring ecosystems. Yet many countries currently lack monitoring programmes that can generate indicators of biodiversity at these scales. Localised monitoring (e.g., 1 km^2) is often amalgamated into national-scale indicators, however, this leaves a substantial gap in the middle of this spatial gradient, limiting availability of information at decision-relevant scales. Here, using the United Kingdom as a case study, we explored the suitability of seven sources of biodiversity data which could be used to construct landscape-scale indicators. We surveyed 70, mostly UK-based, monitoring experts for their opinions on structured and unstructured in-person surveys, camera traps, eDNA, drones, passive acoustic recorders, and satellite remote sensing. We assessed data source utility to construct indicators reflecting Essential Biodiversity Variables, i.e., as holistic measures of

taxa or ecosystems rather than assessments of individual management interventions. All seven data sources were deemed suitable, and experts expected developments in technology and infrastructure to greatly increase this potential over the next decade. However, there are technical, analytical, logistical and financial barriers to establishing monitoring networks that could yield the requisite data for landscape-scale indicators. Resolving these issues requires substantial research, policy commitment and investment, but landscape-scale indicators will be essential for the UK to undertake adaptive management and monitor nature recovery.

Keywords: Autonomous data collection, Biodiversity monitoring, Conservation technology, Remote sensing, Survey methods

Introduction

Biodiversity monitoring evidence is often gathered to reflect Essential Biodiversity Variables (EBVs; Pereira et al., 2013) such as taxonomic diversity or abundance. This evidence can be complex, potentially comprising diverse data types and spanning a wide range of spatiotemporal scales. Monitoring data therefore need synthesising into biodiversity indicators reflecting the state of taxa or ecosystems, to maximise utility for policymaking, land-use planning, and adaptive management (Dale & Beyeler, 2001; Dietze et al., 2018; Gregory et al., 2005; Stephenson, 2020). Monitoring - and the derived indicators - will ideally match the spatial scale of proposed management, intervention or policy (McVittie et al., 2023).

There are a growing number of projects and initiatives, involving combinations of landowners, eNGOs, community stakeholders and statutory bodies, that are aligning their land management to meet shared goals (e.g., Gullett et al., 2023). So, although managers retain control over land use decisions on individual holdings, management is increasingly planned at landscape-scales, (i.e., over areas typically larger than individual land holdings but smaller than regional or national scales). Taking the UK as an example, 'landscape-scale' is in the range of 100s-1000s km^2 (Table 1).

However, at least in the UK, biodiversity indicators are generally calculated at large, often national scales (e.g., the native breeding wild bird population indicator; (Defra, 2025). These are commonly underpinned by site-scale monitoring, such as the 1 km^2 grid squares covering a stratified random sample of the country in the UK's Breeding Bird Survey or National Plant Monitoring Scheme. Yet there is a gap between the two extremes of this spatial gradient. Often, regional- or national-scale indicators cannot be downscaled to landscape scales, as outputs typically have much greater uncertainty (Boyd, Bowler, et al., 2024). Hence – in common with many countries – the UK lacks landscape-scale indicators that would allow effective assessment of protection and restoration efforts.

The absence of landscape-scale indicators in the UK is particularly pertinent given the government has committed to the Kunming-Montreal Global Biodiversity Framework (GBF). Signatories are required to reduce and halt biodiversity decline by the end of this decade, including meeting the '30 by 30' target of protecting 30% of land and seas by 2030. Many governments have indicated they will achieve '30 by 30' via a combination of protected sites, areas within designated landscapes, and Other Effective area-based Conservation Measures (OECMs; Table 1). Ensuring these areas are genuinely contributing to statutory targets will require an increase in monitoring efforts at landscape scales.

In addition to reporting the state of nature in line with statutory requirements and obligations such as the GBF '30 by 30', landscape-scale indicators could be used in at least four further contexts. First, acting as an early-warning system of landscape-scale biodiversity declines. Second, tracking progress of landscape-focussed agri-environment programmes. Third, providing wider context, so that individual landowners can compare biodiversity on their landholdings against that in their local landscape or some other benchmark. And fourth, by facilitating spatially-targeted conservation actions, allowing forward planning, informing design, implementation, efficacy assessment and adaptive management cycles (Conservation Measures Partnership, 2025).

Yet increasing biodiversity monitoring to generate indicators at finer resolutions over wider areas than is currently done will require substantial financial and logistical support. Unfortunately, many government agencies are under financial pressure (Perino et al., 2021), which has reduced capacity in both the UK and other countries to fulfil statutory obligations to monitor the existing designated sites network (OEP, 2025a; Stephenson et al., 2022). This has led to declines in sampling effort over time in many biodiversity monitoring schemes (Lengyel et al., 2018), and makes it unlikely that additional monitoring in areas such as OECMs can be established. To meet the need for increased monitoring at lower costs, governments, agencies and other stakeholders are interested in complementing standardised field-based methods with a range of alternative data sources such as unstructured records from citizen scientists (Fajgenblat et al., 2025; Fraisl et al., 2022) and autonomous technologies (Besson et al., 2022). Generating the requisite data for landscape-scale indicators could be via national schemes with dense sampling which produce datasets that could then be subset to the desired geographical area (i.e., top-down), or through bespoke monitoring networks established at the individual landscape level (i.e., bottom-up) (Affinito et al., 2024).

Here we explore potential data sources available for constructing terrestrial landscape-scale biodiversity indicators. We used a questionnaire to survey mainly UK-based biodiversity monitoring experts who were familiar with a range of data sources, (i.e., data collected with a single method, such as eDNA or camera traps), that could provide the constituent data. In an ideal situation, a suite of biodiversity indicators would encompass variation at all levels from genes to ecosystems (Dale & Beyeler, 2001). However, in the interests of tractability, here we follow most existing monitoring schemes by focussing on species and habitats. We therefore asked experts to assess the suitability of one of four data types: species occurrence or abundance data, and habitat extent or condition. We sought to answer the following questions: (1) Which biodiversity monitoring data types are most readily yielded by widely available data sources? (2) How useful are the resulting data for constructing landscape-scale indicators? (3) In the next ten years, what are the likely developments - such as increased scale of collection or improvements in technology - and how will this affect data utility? The answers to these questions will guide integration of existing data sources and inform the establishment of new monitoring schemes to generate landscape-scale indicators.

Table 1. Areas in the UK where landscape-scale indicators could be used to monitor biodiversity and track progress towards national and international ecosystem recovery targets.

Context	**Description**	**Examples and UK size ranges**
Designated sites	Protected by law, in most cases prioritising nature conservation. In the UK, these align with IUCN protected area Categories III and IV.	• Ramsar (<1 to ≈1,435 km^2) • Special Protection Area (SPA; <1 to ≈1,460 km^2) • Special Area of Conservation (SAC; <1 to ≈1,875 km^2) • SACs and SPAs are also Sites of Special Scientific Interest (SSSI) in England, Wales and Scotland or Areas of Special Scientific Interest (ASSI) in Northern Ireland.
Designated landscapes	Balancing nature conservation against other land-use demands. In the UK, these align with IUCN protected area Categories V and VI.	• National Parks (≈300 to 4,500 km^2) • National Landscapes (≈20 to 2,000 km^2) • National Scenic Areas (≈8 to 1,400 km^2)
Non-designated sites	Other Effective area-based Conservation Measures (OECMs) are effectively managed for nature but specifically not designated as protected areas.	• Candidate OECMs are currently being identified (UK wide, initial sites range from <1 to ≈25 km^2).
Mixed and non-designated landscapes	Landscapes with both designated and non-designated areas.	• Local Nature Recovery Strategies (England-only, ≈350 to 8,300 km^2) • Landscape Recovery Schemes (England-only, ≈5 to 28 km^2)

		• HLF Landscape Partnership Schemes (UK wide, ≈20 to 200 km^2). • Local government areas: Counties, Local Authority Districts (England) Unitary Authorities (England and Wales), Council Areas (Scotland) or District Council Areas (Northern Ireland) (≈16 to 26,000 km^2). • Conservation partnerships with multiple landowners (e.g., Cairngorms Connect 600 km^2; Cumbria Connect 420 km^2).

Methods

2.1 Effective biodiversity data sources

We identified seven data sources that are widely used to collect biodiversity data: structured and unstructured in-person surveys; camera traps; drones using either visual or thermal infrared cameras; eDNA; passive acoustics; and satellite remote sensing. These sources are all commonly used for biodiversity monitoring and could yield data for landscape-scale indicators (Besson et al., 2022; Kitzes et al., 2021). Although other data collection options are available – such as eNose and robot sensors – these are at a lower technology readiness level. Where technologies are suitable for gathering data in more than one format (e.g., drones can capture imagery and sound), we focused on specific examples (Table 3). Each data source could yield one or more data types (i.e., species occurrence or abundance, habitat extent or condition); examples of the data types gathered by each data source are provided in Table S1.

To assess the seven data sources, we needed to define the criteria that would make them suitable for constructing landscape-scale biodiversity indicators. Essential Biodiversity Variables and derived indicators ought to be insensitive to the contributing data sources. Yet, inevitably, indicators are dependent on monitoring approaches, sampling strategies, and analytical approach. Effective biodiversity indicators meet a range of criteria (Dale & Beyeler, 2001; Gregory et al., 2005), the majority of which stem from the underlying data (Table 2). Some of these criteria are essential while others are desirable, and there are inevitably compromises involved when assembling these metrics. Indicators should reflect changes to the composition, structures and functioning of an area's ecosystem over time, but capturing this complexity needs to be balanced against sufficient simplicity to allow straightforward and routine monitoring and reporting (Dale & Beyeler, 2001). Critically, indicators should be sensitive to environmental stressors, responding in a predictable and consistent manner over time (Dale & Beyeler, 2001).

Table 2. Desirable and essential criteria of biodiversity indicators, adapted from Gregory et al (2005) and Dale & Beyeler (2001). Criteria in the 'Input data', 'Numeric properties' and 'Temporal properties' categories depend on the indicator's constituent data. 'Likely to change?' reflects assessment by authors of this study as to whether criteria are sensitive to developments in data sources (e.g., increased spatiotemporal scale of data collection or improvements in technology), or whether they reflect inherent characteristics of the data type (e.g., occurrence rather than abundance data) or the indicator methodology.

Category	**Criteria**	**Essential or desirable?**	**Details**	**Likely to change?**
Input data	Representative	Essential	Low bias in spatial, temporal, and taxonomic coverage (i.e. covering all species in a chosen taxon, or a representative sample).	Yes – greater potential with the likely increases in spatial, temporal, and taxonomic coverage.
	Realistic	Essential	Quantitative data are available or can be readily collected, without requiring excessive or unrealistic financial resources.	Yes – hardware improvements will reduce costs for many data sources.
Numeric properties	Quantifiable	Essential	Indicator is accurate, with an assessment of error. Genuine reflection of trends over time, with a measurable rate of change and changes in that rate.	No - a function of data type and indicator methodology.

	Robust	Essential	Consistently accurate and precise over time and across space (i.e., low bias)	Yes – accuracy and precision are likely to increase with refinements in hardware.
	Stable	Desirable	Impervious to large, irregular, natural fluctuations.	No – a function of indicator methodology rather than data collection per se.
	Dissectible	Essential	Data can be disaggregated to elucidate underlying patterns and shed light on potential drivers of trends.	No - a function of data type and indicator methodology.
Temporal properties	Regular	Essential	Can be updated frequently, on at least an annual basis.	Yes – reduced costs and greater storage capacity will allow more regular data collection.
	Responsive	Essential	Sensitive to stresses and environmental change in a predictable manner, over relatively short time-scales.	No - a function of data type that should remain consistent.
Output	Simple	Desirable	Transparent presentation of complex information, to communicate key messages and ensure impact.	No – a feature of indicators rather than constituent data types.
	Intuitive	Desirable	Easily understood by non-experts, so that they can grasp the issues and take ownership of them.	No – a feature of indicators rather than constituent data types.

	Indicative	Desirable	Represents more general components of biodiversity than just the constituent species' trends, and ideally reflects ecosystem health. And in an anticipatory manner – signifying impending ecological change.	No – a feature of indicators rather than constituent data types. Although this may improve indirectly via increases in the Representative criterion.
	Relevant to policy and management	Essential	Developed in response to stakeholders' needs. Able to inform policy makers in development and review of policy, and to predict changes that can be averted via management.	No – wider uptake and acceptance of novel data sources and data types is likely, but only an indirect consequence of improvements.

2.2 Expert assessment of data sources for landscape-scale biodiversity indicators

Assessment of the seven data sources was via questionnaire implemented using a Google form (available in SI Appendix 1). We approached topic experts via our research networks and employed snowball sampling, where respondents recommended other experts who could be invited to complete the questionnaire. We invited a total of 100 topic experts to participate, specifically highlighting the landscape-scale context of this work. All experts had substantial experience deriving biodiversity data from at least one of the data sources, the majority in a UK context. Submissions were collected between November 2023 and February 2024, and experts who completed the questionnaire were given the opportunity to join the author team.

Experts were asked to select a single data source with which they were most familiar, and we sought a balanced number of responses across the data sources. Experts assessed their chosen data source against the criteria listed in Table 2 for the data type they considered most likely to be gathered. Ratings used a nine-point ordinal scale ranging from 'Terrible' to 'Ideal'; we selected nine levels to give an appropriate granularity of responses. Using a free text box, we asked for opinions on the major developments that could occur in the next 10 years which might alter the suitability of the chosen data source for constructing landscape-scale biodiversity indicators. Potential developments might include hardware, analytical techniques, infrastructure, and economic investment, amongst others. Themes in these free-text answers were grouped by the first author, to identify the development areas deemed most important for each data source. Experts gave their assessment of the likelihood of these developments occurring on a seven-point ordinal scale ranging from 'Very unlikely' to 'Definite'. Finally, experts were asked to imagine it was 2035 (i.e., 10 years in the future), assume the developments they identified had taken place, and reassess the suitability of their chosen data source for landscape-scale biodiversity indicator construction. Although there was the possibility for experts to be biased in favour of their focal data source, their wealth of knowledge and experience meant that they were best placed to provide a genuine assessment of the strengths, weaknesses and potential.

Not all indicator criteria will change with adjustments in data collection, so we focus on those criteria that would alter over time (Table 2). We termed these four key criteria the '4Rs': Realistic, Regular, Representative, Robust. Realistic reflects affordability of data collection; Regular indicates whether data can be collected at intervals sufficient to detect change; Representative refers to whether an indicator covers all species (or habitats) in a landscape or a representative sample thereof; and Robust denotes whether patterns are captured in the same way everywhere (i.e., both within and among landscapes).

We used Bayesian ordinal regression to analyse patterns in questionnaire responses, implemented with the 'brms' package in R (Bürkner, 2017; R Core Team, 2024). We ran a separate model for each of the '4Rs' criteria, assessing suitability among data types and over time, with rating as the response, and data type and year (i.e., 2025 vs 2035) as categorical predictors with a random intercept for expert. We ran a fifth model examining likelihood of developments in the next 10 years, with rating as the response, data source as the predictor and a random intercept for expert. For all models we ran four chains, each with 4000 iterations, 2000 iterations discarded during warm up, and a thinning rate of 10 to give 800 posterior samples per model. We checked traceplots, Rhat, and ESS values to confirm models converged successfully, and extracted predictions via the brms function 'epreds'.

Results

3.1 Which biodiversity monitoring data types are most readily yielded by widely available data sources?

We received 70 questionnaire responses (i.e., a 70% response rate). Experts were employed by a range of conservation non-governmental organisations (NGOs, n = 17), universities (17), research institutes (16), statutory agencies (12), and commercial companies (8). Experts were largely based in the UK (67 of 70 respondents). There were between 7 and 17 responses per data source (Figure 1). Irrespective of data source, most experts viewed species occurrence as the most readily acquired data type (50 of 70; Figure 1). This included all of the responses received for camera traps (11), eDNA (10), passive acoustics (10) and unstructured in-person surveys (17), but none from satellite remote sensing (7).

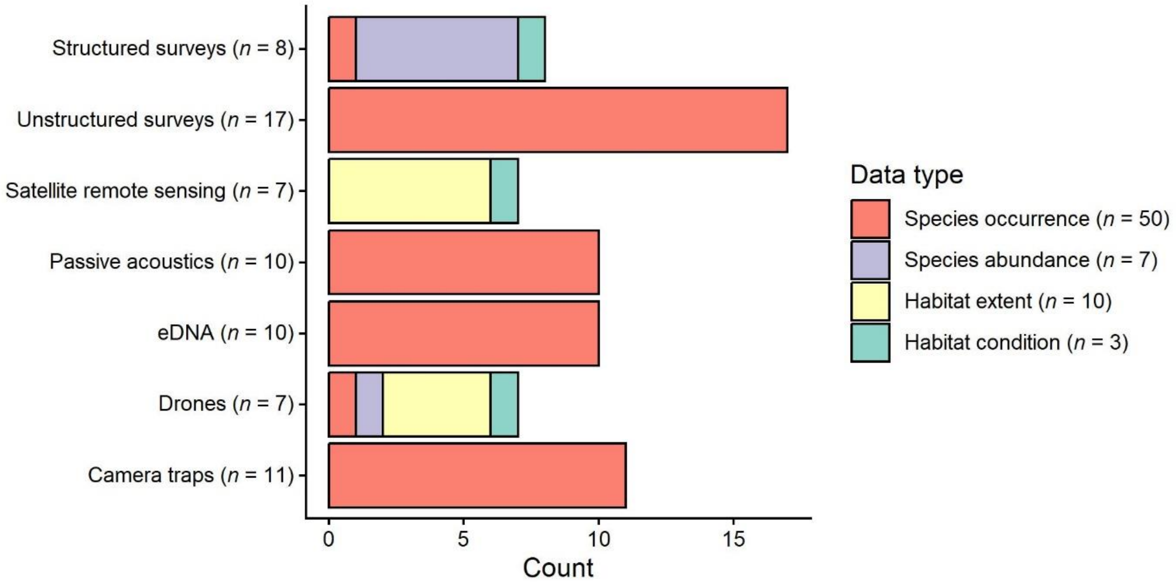

Figure 1. Numbers of questionnaire responses for each data source divided by data type. Surveyed experts selected a single data type they deemed to be the one most readily collected with their selected data source, although most sources can produce more than one data type (see examples in Table S1).

3.2 How useful are the resulting data for constructing landscape-scale indicators?

All data sources were considered to yield data suitable to construct landscape-scale indicators that met the criteria listed in Table 2 (Figures 2 and S1). We summarised which taxa or habitat metrics can be surveyed with each data source in Table 3, based on examples mentioned by experts in the free-text responses in the questionnaire and our knowledge of the literature (Table S1).

The '4Rs' criteria (Realistic, Regular, Representative and Robust; Table 2) were already rated fairly highly in 2025 for all four biodiversity data types (Figure 2), a trend borne out by the model predictions. Modal scores (both raw counts and predicted medians from the models) were generally "Quite good" or above (7 or more out of 9). The same responses divided by data source instead of data type are in Figure S2 and show similarly positive assessments. A plot for the remaining eight criteria that are unlikely to change with future developments are in Figure S1 separated by data type. Almost all raw responses for these criteria were "Potentially suitable" or better (scored 5 or more).

Table 3. Suitability of seven data sources for monitoring a range of taxa (either occurrence, abundance or both) and habitat extent and condition. Assessment of suitability based on questionnaire responses and published literature (examples in Table S1). Level of suitability indicated by '✓' (ideal) or '(✓)' (potentially suitable depending on species or context).

Data source	**Micro-organisms**	**Fungi**	**Invertebrates**	**Amphibians**	**Reptiles**	**Birds**	**Mammals**	**Plants**	**Habitat extent**	**Habitat condition**
Structured or semi-structured surveys		✓	✓	✓	✓	✓	✓	✓	✓	✓
Unstructured surveys		✓	✓	✓	✓	✓	✓	✓		(✓)
Satellite remote sensing using hyperspectral, radar, or LiDAR.							(✓)	(✓)	✓	✓
Passive acoustic monitoring			(✓)	✓	✓	✓	✓			(✓)
eDNA	✓	✓	✓	✓	✓	(✓)	(✓)	(✓)		(✓)

Drones using visual or thermal infrared cameras.						(✓)	(✓)	✓	✓	✓
Camera traps			✓	✓	✓	✓	✓			(✓)

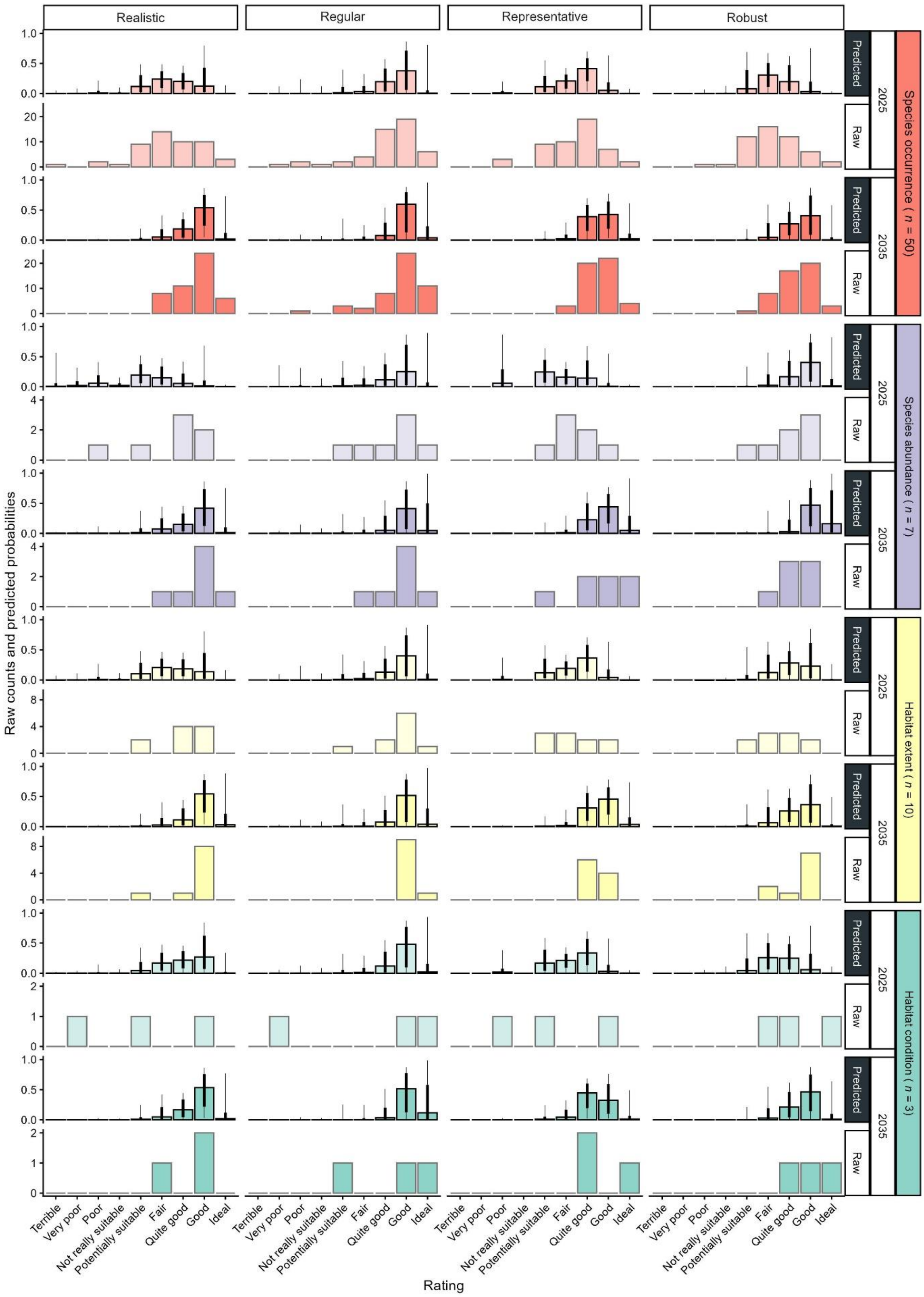

Figure 2. Experts' assessment of suitability in the '4Rs' criteria (Realistic, Regular, Representative and Robust) for the seven data sources to construct landscape-scale indicators based on four data

types. Assessments were on an ordinal scale: 1 = 'Terrible', 5 = 'Potentially suitable, 9 = 'Ideal'. Light bars are assessments for 2025, dark bars for 2035. Predicted median probabilities are outlined in black with 50% and 89% credible intervals indicated by the thick and thin vertical lines respectively. Counts of raw scores are outlined in grey; note y-axes differ among the raw count plots. Equivalent figure for the remaining eight criteria deemed unlikely to change because of technological and infrastructure developments is in Figure S1 with raw counts only.

3.3 What are the likely developments - such as increased scale of collection or improvements in technology - in the next ten years, and how will this affect data suitability?

All respondents agreed that changes in infrastructure, hardware or analyses could improve the data quality from all seven data sources. These changes would likely lead to improvements in landscape-scale indicators constructed from such data, according to our criteria (Table 2).

All experts expected developments in their chosen data source to occur in the next 10 years, with modal raw and predicted scores of either "Quite possible" or "Almost certain" (ranked 5 or 6 out of 7; Figure 3). Every expert provided free-text responses outlining the developments, in most cases these answers included statements on more than one area where they expected progress. There were 185 statements in total, which the first author categorised into five themes: data collection, data analysis, data management, hardware, and broader context (reflecting economic investment and skills development) (Table 4). Notable developments considered likely to occur in four or more of the seven data sources included: broader taxonomic coverage, improved temporal coverage, and greater opportunity to derive abundance data (data collection); data integration (data analysis); data archives, repositories, and metadata standards (data management); new sensors and hardware, and incorporation of artificial intelligence (hardware). A full list of the factors mentioned by experts are listed in Table S2. Experts anticipated that the developments would further improve the suitability of the '4Rs' criteria. Nearly all 2035 predicted scores rose to "Good" (8 out of 9; Figure 2) for Realistic, Representative and Robust. Regular had the highest rankings of the ‘4Rs’ in 2025, but these increased only slightly in 2035.

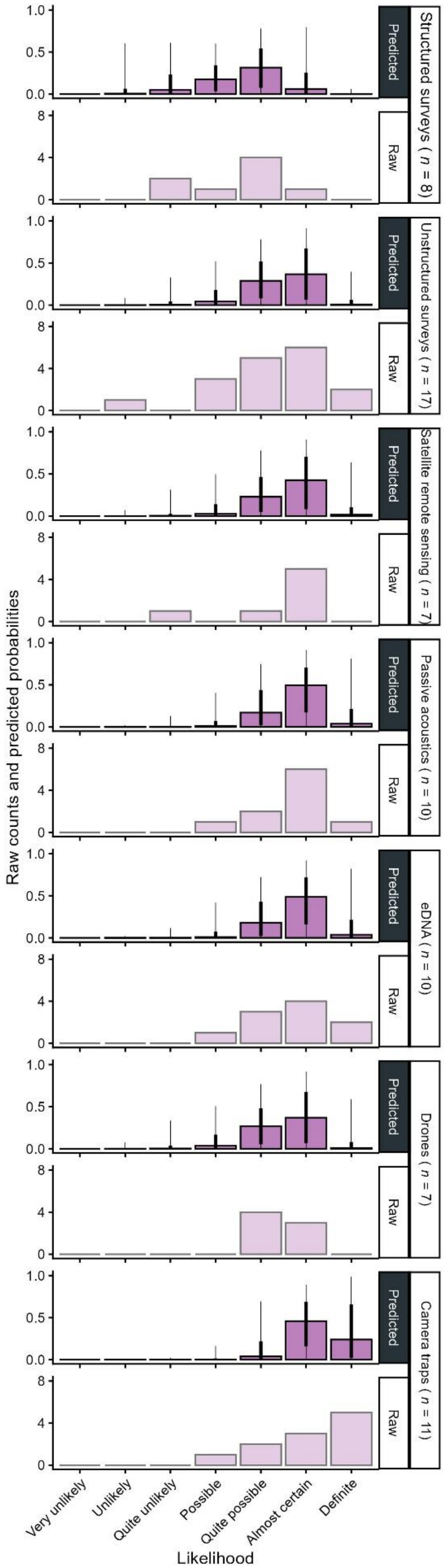

Figure 3. Experts' assessment of the likelihood of technological and infrastructure developments over the next decade for a range of data sources that could be used in landscape-scale biodiversity indicators. Predicted median probabilities are shown in darker bars with 50% and 89% credible intervals indicated by the thick and thin vertical lines respectively; counts of raw ratings are in shown with paler bars outlined in grey.

Table 4. Major developments thought likely to occur in the next decade that might improve the suitability of data sources for landscape-scale biodiversity indicators. " '4Rs' criteria" identifies those which are affected by each development. A tick indicates that the development was identified by at least one expert; full lists of the factors mentioned are in Table S2. Absence of a tick implies experts viewed the development as either (a) irrelevant as the data source is already at a mature stage in that respect, (b) relatively less important, or (c) unlikely to be achievable.

Area	**Development**	**'4Rs' criteria**	**Structured surveys**	**Unstructured surveys**	**Satellite remote sensing**	**Passive acoustics**	**eDNA**	**Drones**	**Camera traps**
Data collection	Streamlined data collection methods	Realistic, Regular	✓	✓					
	Broader taxonomic coverage	Representative	✓	✓		✓			✓
	Broader geographic coverage	Robust	✓				✓		

	Improved temporal coverage	Representative		✓	✓	✓	✓		
	Deriving abundance data (for more taxa)	Representative	✓			✓	✓		✓
	Standardised sampling and monitoring guidance	Robust				✓	✓	✓	
Data analysis	Improved modelling approaches	Robust	✓	✓		✓			
	Data integration, integrate models	Representative, Robust	✓	✓		✓	✓		
Data management	Cloud computing and remote data transfer	Realistic, Regular			✓	✓			✓
	Data archives, repositories and metadata standards	Realistic		✓	✓	✓	✓		
Hardwa	New sensors and improved hardware	Representative, Realistic			✓	✓	✓	✓	✓

	Lower hardware costs	Realistic, Regular				✓	✓	✓	
	Artificial Intelligence approaches	Realistic, Regular		✓	✓	✓		✓	✓
Broader context	Economic investment	Realistic	✓	✓	✓				
	Skills development, citizen scientist recruitment and retention	Realistic	✓		✓				

4 Discussion

4.1 Questionnaire responses

We asked monitoring experts to assess the potential of seven widely used data sources for constructing terrestrial, landscape-scale biodiversity indicators. Experts considered species occurrence data to be most readily collected at present, with fewer opportunities for gathering data on species abundance, habitat extent or condition. In part this reflects the development stage of data sources such as passive acoustics and eDNA, as these can only generate occurrence data for now. This limits the scope of the Essential Biodiversity Variables that can be measured with these data sources, precluding metrics such as species abundance, community abundance, and ecosystem structure. This restricts the contribution such data sources can make to abundance-based indicators required for statutory targets such as those specified in England's Environment Act. Although it should be noted that for some taxonomic groups, such as fungi, abundance metrics may not be as ecologically meaningful for management. Experts highlighted that developments in those data sources should lead to increased opportunities for abundance data and so improve suitability in the longer term. In the meantime, new or expanded structured surveys could provide the necessary data for a wider suite of EBVs (Proença et al., 2017; Schmeller et al., 2015).

All seven data sources were deemed suitable for generating data for use in landscape-scale indicators according to our predefined criteria. To some extent this reflects our *a priori* selection of mature data sources (i.e., for automated methods, those with high technological readiness levels), so that all are already suitable for gathering biodiversity data. However, there was a consensus amongst experts that these data sources can and will contribute to landscape-scale indicators.

Experts believed suitability of all data sources would improve further over the next decade with developments in hardware, and collection, analysis, and management of data. Of the '4Rs' indicator criteria, the potential for data collection to be 'Regular' was already given consistently high scores with only marginally increased ratings likely by 2035. Automated technologies such as passive acoustics and camera traps already offer high temporal resolution sampling, and experts predicted greater temporal coverage in the future would improve suitability for unstructured surveys and satellite remote sensing. New sensors and hardware improvements were predicted to improve all automated technologies, while developments in data processing using AI were also important for all data sources except structured surveys and eDNA. Realising the potential of many of these data sources for landscape-scale indicators will require substantial analytical developments, policy support and financial investment in the years ahead.

Despite our best efforts to achieve an equal sample across all data sources we did have some imbalance, with higher numbers of experts assessing unstructured surveys (n = 17), compared to satellite remote sensing and drones (both n = 7). This led to wider credible intervals for the latter in the data source improvement model, indicating greater uncertainty in the posterior. However, while we can expect that broader sampling coverage would lead to improved precision in these estimates, the overall assessment remains positive regardless.

4.2 Maximising utility of diverse data sources

Experts' assessments were only for individual data sources and so reflect specific spheres of knowledge rather than comparisons between alternative approaches to gathering data. This prevented an assessment of data source complementarity. Yet combining multiple data sources could emphasise the strengths of different data sources; for example, integrating the spatial coverage of satellite remote sensing with the high temporal resolution of passive acoustic monitoring. This could give a much fuller picture of the state of biodiversity (Cavender-Bares et al., 2022; Hartig et al., 2024), which could lead to more informative landscape-scale indicators covering a broader range of taxa.

Realising effective synthesis of multimodal data or multiple datasets to generate landscape-scale biodiversity indicators requires further development of integrated models. Experts expected improvements in integrated models would increase data source suitability, particularly for incorporating structured survey data with occurrence data from unstructured surveys, acoustics and eDNA. Integrated models can provide refined population estimates if the models are well-specified

(Isaac et al., 2020) but potentially poorer insights when they are not (Seaton et al., 2024). These models are under active development and there remain substantial challenges around model validation and amalgamation of data from different sources collected using different methods (Boyd, August, et al., 2023; Johnston et al., 2022). This is particularly acute when integrating data across multiple taxa, which often come from different data sources (Boyd, August, et al., 2023; Kissling et al., 2018). Resolving these issues would likely lead to greater adoption of additional data sources and so leverage their complementarity.

Our questionnaire responses highlighted the widespread potential to gather species occurrence data. Occurrence records can permit exploration of temporal biodiversity patterns that would otherwise be impossible to study (Outhwaite et al., 2020; Outhwaite et al., 2019). Hence, it could be useful to further invest in occurrence-based biodiversity indicators (Boyd, August, et al., 2023), and there are currently distribution-based indicators for priority species, and for pollinators in the UK (JNCC, 2024). Occurrence-based indicators could be useful in a range of cases including: broadening taxonomic coverage; monitoring Invasive Non-Native Species, where distribution may be more important than abundance; or monitoring assemblages with many rare species (Enquist et al., 2019), which are often those at greatest risk of extirpation (Matthies et al., 2004).

However, there are practical constraints to adopting more occurrence-based indicators – in terms of financial costs, processing demands, and analytical challenges – that could limit their potential, and these issues will become more acute with the expansion of occurrence data collection efforts. When different datasets begin at different times it can be complicated to compare new trends with historic ones (Freeman et al., 2020), and with unstructured survey protocols there are also substantial concerns around correcting for variation in sampling effort in both time and space (Boyd, Stewart, et al., 2024). Finally, while occurrence-based indicators offer potential, this may only be true at coarser spatial resolutions (Boyd, Bowler, et al., 2024), they may also be less responsive (Falaschi et al., 2025), be unsuitable for widely distributed species, and may even give counterintuitive signals should species ranges increase while abundances decline (Gregory, 1998; Nakagawa et al., 2025). These issues have implications for management and policy; will we still be able to reliably detect biodiversity change?

Species abundance data derived from structured surveys will likely remain important to provide early warning systems and corroborate occurrence trends for the foreseeable future. Experts predicted improvements in structured survey data would come from streamlined data collection methods and broader taxonomic coverage in particular.

4.3 What would a monitoring network for landscape-scale indicators look like?

Generating landscape-scale indicators typically requires large, representative sampling to gather sufficient biodiversity data (Lohr, 2021). Good survey design principles (i.e., sampling strategy and analyses), data storage, and processing infrastructure are all required to convert those data into indicators. Determining the most appropriate data sources, data types and spatiotemporal sampling resolution will depend on the chosen taxa or features, management aims and reporting requirements (Ockendon et al., 2026). Scoping studies and power analyses would provide clarity in specific situations. Co-locating sampling to gather data on multiple taxa from the same points should result in more useful and representative indicators. High accuracy is necessary if indicators are to provide early-warnings of landscape-scale biodiversity trends and allow land managers to use adaptive management (Ockendon et al., 2026; Watts et al., 2020).

Monitoring networks could be established through bottom-up (i.e., landscape-level) or top-down (i.e., national) approaches (Affinito et al., 2024). In the short term, bespoke paradigms for individual landscapes are likely to be more achievable. One UK example of this uses citizen science approaches to gather co-located data on birds, butterflies and vascular plants (Chilterns Conservation Board, 2025). A more ambitious alternative to monitoring individual landscapes would be a standardised, national-scale sampling network stratified across landscape units. This would be more flexible, providing consistent national trends which could be subset to generate biodiversity indicators at a range of spatial scales or locations as required using small area estimation techniques (Rao & Mollina, 2015). In the UK, only satellite remote sensing currently provides the combination of geographical coverage with sufficiently dense sampling for generating landscape-scale habitat indicators in this way (Marston et al., 2023). Many other national-scale biodiversity monitoring networks exist in the UK, such as structured surveys for specific taxa like the UK Breeding Bird Survey (Massimino et al., 2025). However, these typically lack the requisite sampling density to permit landscape-scale sub-setting without introducing substantial uncertainty.

Regardless of the geographic scope, establishing a monitoring network requires substantial investments in data gathering, coordination capacity, data infrastructure, and analytical resources. Although innovations will likely reduce sensor and data costs in the future, installation and maintenance of automated devices often requires considerable amounts of time and money. There are few analyses exploring the relative time demands of using these technologies versus in-person sampling methods (e.g., Jarrett & Willis, 2024; Roberts, 2011), nor are there many studies comparing the temporal efficiencies of multiple technologies with one another (Bell & Malerba, 2025; Hoefer et al., 2025). A scoping study of relative time and equipment costs would be a valuable feasibility exercise, as financial and logistical issues currently represent fundamental barriers to widespread adoption of newer monitoring technologies at a level sufficient to realise landscape-scale biodiversity indicators. This would need to encompass the practicalities associated with automated data management and analysis pipelines, as most data sources generate enormous volumes of data which cannot easily be reviewed manually (Roe et al., 2021; Teixeira et al., 2024).

Beyond the practical challenges of establishing landscape-scale monitoring, there are wider issues around acceptance and funding. Policy makers already recognise the potential that including a range of data sources could have in constructing landscape-scale biodiversity indicators. Yet governments and statutory agencies are often reluctant to adopt these approaches. In the UK, statutory agency budgets have been reduced such that they struggle to adequately cover existing statutory monitoring responsibilities (OEP, 2025a, 2025b), and budgets could be lowered further in future. Hence agencies often have fewer opportunities for testing alternatives, and there may be a reluctance to invest in new approaches and indicators that could be subject to future financial reductions.

4.4 Alternative options for landscape-scale biodiversity indicators

Given the challenges associated with establishing and maintaining biodiversity monitoring networks, it could be desirable to adopt indicators that require fewer data to construct and would therefore be available sooner and at lower costs without establishing additional bespoke schemes. Here, we consider examples of potential data summary metrics that could be adopted for landscape-scale biodiversity indicators based on current levels of monitoring.

4.4.1 Simple measures

Occurrence data extracted from in-person surveys, camera traps, acoustics, drones and eDNA can be readily converted to basic biodiversity metrics such as species richness. Counts of species are relatively simple to assemble and are readily interpretable by non-scientists, and species richness measures have been widely utilised in landscape-scale contexts (e.g., Yorkshire Wildlife Trust, 2024). However, general measures of species richness are widely criticised as an indicator of biodiversity; notably they do not reflect rarity and are impervious to turnover (Fletcher et al., 2025; Lamb et al., 2009). A pristine assemblage of specialist or rare species could be completely replaced with common, generalist or invasive species, but richness would remain the same despite shifts in ecosystem functioning (Hillebrand et al., 2018). This makes it impossible to draw conclusions from comparisons across space or over time. Narrowing the metric to threatened or priority species can therefore be more meaningful (see below). Regardless, in many cases, richness estimates are subject to error from imperfect sampling, and unquantified biases from failing to account for imperfect detection (Boyd, Powney, et al., 2023; Fletcher et al., 2025), limiting their value as indicators.

Equivalent simple measures for habitats are often based on habitat extent and configuration. For example, satellite remote sensing data provides estimates of broadscale changes in landcover (Hansen et al., 2013; Rowland et al., 2020) and habitat condition (Kacic et al., 2023). Using optical satellite data, metrics of habitat condition based on proxies such as the normalised difference vegetation index (NDVI) or enhanced vegetation index (EVI) are also possible (Manes et al., 2010).

Such measures can be tracked over time (Matas-Granados et al., 2022) and can be calibrated to biophysical variables such as net primary productivity using field data (Tebbs et al., 2017). Validation of such proxies generally relies on in-person surveys, which may be achievable in individual landscapes, but could be challenging for a national scheme.

4.4.2 Exemplar species or habitat features

Rather than attempting a complete inventory of all species, proxies may be used to reflect overall ecosystem health. Again, occurrence data from in-person surveys, camera traps, acoustics and eDNA could be exploited for this purpose. There is an extensive history of using individual species or taxa as proxies or 'indicator species' (Gregory & van Strien, 2010; Simberloff, 1998). Taxa have often been selected because long data series already exist, and while there are notable successes with this method (Brlik et al., 2021; van Swaay et al., 2008), there is also the potential for taxonomic bias. Selecting several complementary exemplar groups is therefore critical, as responses to land use and land use change often vary within-taxon and among-taxa (Bradfer-Lawrence, Dobson, et al., 2025; Mancini et al., 2023).

Focussing on particular groups of threatened or range-restricted species circumvents some of the issues that weaken utility of overall species richness measures (Fletcher et al., 2025). Indicator taxa may therefore better reflect the importance of an area for biodiversity and can be substantially more tractable than attempting a comprehensive survey. Examples of this approach in the UK include a long-term landscape restoration project covering 600 km^2 in the Scottish Highlands, which monitors birds, macro-moths and ericaceous shrubs (Cairngorms Connect, 2025; Gullett et al., 2023).

There are numerous indicators designed to reflect habitat-specific condition. For example, Woodland Ecological Condition surveys (Ditchburn et al., 2020) combine 15 metrics of forest attributes likely to reflect biodiversity value, while the Forest Biodiversity Index (Bellamy et al., 2024) incorporates structural measures from the surrounding landscape as well. Inputs are often a blend of remote sensing and in-person datasets. Alternatives such as the Habitat Condition Index

(Knight et al., 2021) rely exclusively on data gathered remotely, although validation would likely require in-person surveys (Cavender-Bares et al., 2022; Lawley et al., 2016).

The Nature Index (Certain et al., 2011) takes the exemplars approach further, combining records from multiple data sources with expert opinion for individual species, species groups and habitat features. The status of each component feature is assessed against a pre-determined baseline, (not necessarily a hypothetical 'natural' or 'pristine' state). Each feature feeds into a series of spatially explicit indicators that can be further aggregated into a single metric. In the UK, this approach has been adopted by the Cairngorms National Park Authority who use around 200 species and habitat features over six major ecosystems to provide a summary metric for each major catchment in the National Park. Despite focussing on a subset of species and habitat features and using preexisting data, this approach can still be constrained given the amounts of dataset preparation and integration required.

4.4.3 Modelled indicators

The last group of potential indicators uses modelling to predict the status of component features even where no data have been collected (Bowler et al., 2024). Modelling approaches can, in theory, circumvent the issues with limited or biased sampling that hampers the other indicator options presented above, provided that site or species residuals are independent of the original sampling process (Boyd et al., 2025; Boyd, Stewart, et al., 2024). If enough underpinning data are available and models are sufficiently accurate, this could offer a route to landscape-scale indicators without requiring a landscape-scale monitoring network.

4.5 Wider context and conclusions

The indicator framework we adopted here, and particularly the '4Rs' criteria that are likely to change with data source developments, are equally applicable in other countries. Our results are based on a UK context; a small, relatively resource-rich but biodiversity-poor country with a long history of monitoring and its attendant infrastructure. Assessments in other European nations might yield similar patterns to those we report here. However, undertaking similar studies in other settings would very likely result in context-specific findings.

For countries with large areas of relatively undisturbed habitat, or limited funding for monitoring, or both, using some of the data sources we assessed may be unrealistic. Larger high-income countries may be able to resource extensive monitoring networks but face additional logistical challenges from long distances, remote settings, and managing very large datasets (Brunk et al., 2025; Roe et al., 2021; Rooney, 2025). Moreover, even in relatively wealthy countries, funding for monitoring is frequently at risk, which can lead to efforts being scaled back (Lengyel et al., 2018).

While suitability of data sources ought to be universal, the barriers to deployment and subsequent analysis and generation of landscape-scale indicators are likely to be more challenging for low- and middle-income countries. Inequities have led to spatiotemporal data gaps that limit indicators' historical scope, while resources remain limited and contemporary monitoring is often sparse (Chapman et al., 2024; Dove et al., 2023; Stephenson, 2020). Thus, unstructured surveys and satellite remote sensing may remain the most feasible options for many low- and middle-income countries in the near-term. Making progress will require substantial in-country investment, otherwise encouraging shifts towards data sources that necessitate analytical facilities only available outside of a country merely cements environmental data injustices (Bradfer-Lawrence, Burivalova, et al., 2025; Chapman et al., 2024). Yet, if these barriers can be overcome with sufficient funding and capacity building, then developments may make an even greater difference to biodiversity monitoring in low- and middle-income countries.

Commitments to the GBF's targets including '30 by 30' has led to increased interest from governments and statutory agencies in how to measure progress towards recovering species and habitats. Questions remain around how this can be achieved over much larger areas at finer scales than covered by current monitoring schemes. While all seven data sources we assessed are suitable for gathering biodiversity data, translating this potential into landscape-scale indicators will require substantial investment in analytical developments, data infrastructure and coordination, and acceptance by policymakers.

Ethics

This study received approval from the RSPB's ethics committee, 5th September 2023.

Competing interests

The authors have no competing interests to declare that are relevant to the content of this article.

Data availability

Questionnaire scores and R code will be deposited in a publicly-accessible repository upon acceptance.

Funding

This research did not receive any specific grant funding.

Acknowledgements

Our thanks to all the questionnaire respondents: Tom August, Diana Bowler, Andrea Britton, Katie Clark, Jeremy Cusack, Emily Dennis, Alice Edney, Felicity Edwards, Pippa Howard, Harriet Knafler, Stuart Newson, Robin Pakeman, Helen Rees, Phillip Stephens, Andy Taylor, Kevin Walker, Simon Wotton, Richard Wilson, Robin Whytock, and twenty-one others who preferred to remain anonymous. We are grateful to members of the RSPB Four Country Sites Policy Group, for their insight and guidance during the development of this project.

CRediT author statement

Tom Bradfer-Lawrence: Conceptualization, Methodology, Formal analysis, Writing – original draft **Meriel Harrison**: Conceptualization, Writing - Review & Editing, **Adham Ashton-Butt**: Writing - Review & Editing, **Sophie Bennett**: Writing - Review & Editing, **Robin J. Boyd**: Writing - Review & Editing, **Ella Browning**: Writing - Review & Editing, **Graeme Buchanan**: Writing - Review &

Editing, **Adam Fraser**: Writing - Review & Editing, **Sian E. Green**: Writing - Review & Editing, **Robert Hawkes**: Writing - Review & Editing, **Becky E. Heath**: Writing - Review & Editing, **Pen-Yuan Hsing**: Writing - Review & Editing, **Nick Isaac**: Writing - Review & Editing, **Matthew Jordan**: Writing - Review & Editing, **Francesca Mancini**: Writing - Review & Editing, **Oliver Metcalf**: Writing - Review & Editing, **David T. Milodowski**: Writing - Review & Editing, **David O'Brien**: Writing - Review & Editing, **Rory O'Connor**: Writing - Review & Editing, **Oliver L. Pescott**: Writing - Review & Editing, **Jake M. Robinson**: Writing - Review & Editing, **Clare Rowland**: Writing - Review & Editing, **Sarab S. Sethi**: Writing - Review & Editing, **Mike P. Shewring**: Writing - Review & Editing, **Lin Wang**: Writing - Review & Editing, **Oliver R. Wearn**: Writing - Review & Editing, **David E. Wembridge**: Writing - Review & Editing, **Serge A. Wich**: Writing - Review & Editing, **Paul Woodcock**: Writing - Review & Editing, **Richard D. Gregory**: Writing - Review & Editing, Supervision, **Fiona Burns**: Conceptualization, Writing - Review & Editing, Supervision.

References

Affinito, F., Williams, J. M., Campbell, J. E., Londono, M. C., & Gonzalez, A. (2024). Progress in developing and operationalizing the Monitoring Framework of the Global Biodiversity Framework. *Nat Ecol Evol*, *8*(12), 2163–2171. https://doi.org/10.1038/s41559-024-02566-7

Bell, K., & Malerba, M. E. (2025). Biodiversity monitoring for biocredits: a case study comparing acoustic, eDNA, and traditional methods. *Biodiversity and Conservation*, *34*(7), 2513–2528. https://doi.org/10.1007/s10531-025-03083-0

Bellamy, C., Rattey, A., Edwards, C., Kortland, K., Stringer, A., Tew, E., Bathgate, S., Kerecsenyi, N., Moseley, D., Watts, K., & Broome, A. (2024). The forest biodiversity index (FOBI): monitoring forest biodiversity potential over space and time. *Environmental Research: Ecology*, *3*(3). https://doi.org/10.1088/2752-664X/ad57cf

Besson, M., Alison, J., Bjerge, K., Gorochowski, T. E., Hoye, T. T., Jucker, T., Mann, H. M. R., & Clements, C. F. (2022). Towards the fully automated monitoring of ecological communities. *Ecol Lett*, *25*(12), 2753–2775. https://doi.org/10.1111/ele.14123

Bowler, D. E., Boyd, R. J., Callaghan, C. T., Robinson, R. A., Isaac, N. J. B., & Pocock, M. J. O. (2024). Treating gaps and biases in biodiversity data as a missing data problem. *Biological Reviews*. https://doi.org/10.1111/brv.13127

Boyd, R. J., August, T. A., Cooke, R., Logie, M., Mancini, F., Powney, G. D., Roy, D. B., Turvey, K., & Isaac, N. J. B. (2023). An operational workflow for producing periodic estimates of species occupancy at national scales. *Biological Reviews*, *98*(5), 1492–1508. https://doi.org/10.1111/brv.12961

Boyd, R. J., Bowler, D. E., Isaac, N. J. B., & Pescott, O. L. (2024). On the trade-off between accuracy and spatial resolution when estimating species occupancy from geographically biased samples. *Ecological Modelling*, *493*. https://doi.org/10.1016/j.ecolmodel.2024.110739

Boyd, R. J., Jarvis, S., Meng, X.-L., Powney, G. D., Spake, R., & Pescott, O. L. (2025). A fundamental theory of actual error for species population monitoring. *EcoEvoRXiv*.

Boyd, R. J., Powney, G. D., & Pescott, O. L. (2023). We need to talk about nonprobability samples. *Trends in Ecology & Evolution*, *38*(6), 521–531. https://doi.org/10.1016/j.tree.2023.01.001

Boyd, R. J., Stewart, G. B., & Pescott, O. L. (2024). Descriptive inference using large, unrepresentative nonprobability samples: An introduction for ecologists. *Ecology*, *105*(2). https://doi.org/10.1002/ecy.4214

Bradfer-Lawrence, T., Burivalova, Z., & Dent, D. H. (2025). Deriving meaning from acoustic data in hyper-diverse ecosystems. *Trends Ecol Evol*, *40*(5), 431–435. https://doi.org/10.1016/j.tree.2025.03.004

Bradfer-Lawrence, T., Dobson, A. D. M., Finch, T., Fuentes-Montemayor, E., Hanley, N., Matthiopoulos, J., Nthambi, M., Simpson, K., Watts, K., Whytock, R. C., & Park, K. J. (2025). Spillovers and legacies of land management on temperate woodland biodiversity. *Nat Ecol Evol*, *9*(6), 1009–1020. https://doi.org/10.1038/s41559-025-02688-6

Brlik, V., Silarova, E., Skorpilova, J., Alonso, H., Anton, M., Aunins, A., Benko, Z., Biver, G., Busch, M., Chodkiewicz, T., Chylarecki, P., Coombes, D., de Carli, E., Del Moral, J. C., Derouaux, A., Escandell, V., Eskildsen, D. P., Fontaine, B., Foppen, R. P. B.,…Klvanova, A. (2021). Long-term and large-scale multispecies dataset tracking population changes of common European breeding birds. *Scientific Data*, *8*(1), 21. https://doi.org/10.1038/s41597-021-00804-2

Brunk, K. M., Goldberg, J. F., Maxwell, C., Peery, M. Z., Jones, G. M., Gallagher, L. R., Kramer, H. A., Westerling, A. L., Keane, J. J., Kahl, S., & Wood, C. M. (2025). Bioregional-scale acoustic monitoring can support fire-prone forest restoration planning. *Frontiers in Ecology and the Environment*, *23*(7). https://doi.org/10.1002/fee.2843

Bürkner, P.-C. (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software*, *80*(1). https://doi.org/10.18637/jss.v080.i01

Cairngorms Connect. (2025). *The Cairngorms Connect project*. https://cairngormsconnect.org.uk/

Cavender-Bares, J., Schneider, F. D., Santos, M. J., Armstrong, A., Carnaval, A., Dahlin, K. M., Fatoyinbo, L., Hurtt, G. C., Schimel, D., Townsend, P. A., Ustin, S. L., Wang, Z., & Wilson, A. M. (2022). Integrating remote sensing with ecology and evolution to advance biodiversity conservation. *Nat Ecol Evol*, *6*(5), 506–519. https://doi.org/10.1038/s41559-022-01702-5

Certain, G., Skarpaas, O., Bjerke, J. W., Framstad, E., Lindholm, M., Nilsen, J. E., Norderhaug, A., Oug, E., Pedersen, H. C., Schartau, A. K., van der Meeren, G. I., Aslaksen, I., Engen, S., Garnasjordet, P. A., Kvaloy, P., Lillegard, M., Yoccoz, N. G., & Nybo, S. (2011). The Nature Index: a general framework for synthesizing knowledge on the state of biodiversity. *PLoS One*, *6*(4), e18930. https://doi.org/10.1371/journal.pone.0018930

Chapman, M., Goldstein, B. R., Schell, C. J., Brashares, J. S., Carter, N. H., Ellis-Soto, D., Faxon, H. O., Goldstein, J. E., Halpern, B. S., Longdon, J., Norman, K. E. A., O'Rourke, D., Scoville, C., Xu, L., & Boettiger, C. (2024). Biodiversity monitoring for a just planetary future. *Science*, *383*, 34–36. https://doi.org/10.1126/science. adh8874

Chilterns Conservation Board. (2025). *Tracking the Impact*. Retrieved 26/09/2025 from https://www.chilterns.org.uk/flagship-projects/tracking-the-impact/

Conservation Measures Partnership. (2025). *Open Standards for the Practice of Conservation Version 5.0*.

Dale, V. H., & Beyeler, S. C. (2001). Challenges in the development and use of ecological indicators. *Ecological Indicators*, *1*, 3–10.

Defra. (2025). *Wild bird populations in the UK and England, 1970 to 2024*. https://www.gov.uk/government/statistics/wild-bird-populations-in-the-uk/wild-bird-populations-in-the-uk-and-england-1970-to-2024

Dietze, M. C., Fox, A., Beck-Johnson, L. M., Betancourt, J. L., Hooten, M. B., Jarnevich, C. S., Keitt, T. H., Kenney, M. A., Laney, C. M., Larsen, L. G., Loescher, H. W., Lunch, C. K., Pijanowski, B. C., Randerson, J. T., Read, E. K., Tredennick, A. T., Vargas, R., Weathers, K. C., & White, E. P.

(2018). Iterative near-term ecological forecasting: Needs, opportunities, and challenges. *Proc Natl Acad Sci U S A*, *115*(7), 1424–1432. https://doi.org/10.1073/pnas.1710231115

Ditchburn, B., Wilson, T., Henderson, L., Kirby, K., & Steel, P. (2020). *NFI woodland ecological condition in Great Britain: Statistics*

Dove, S., Bohm, M., Freeman, R., McRae, L., & Murrell, D. J. (2023). Quantifying reliability and data deficiency in global vertebrate population trends using the Living Planet Index. *Glob Chang Biol*, *29*(17), 4966–4982. https://doi.org/10.1111/gcb.16841

Enquist, B. J., Feng, X., Boyle, B., Maitner, B., Newman, E. A., Jørgensen, P. M., Roehrdanz, P. R., Thiers, B. M., Burger, J. R., Corlett, R. T., Couvreur, T. L. P., Dauby, G., Donoghue, J. C., Foden, W., Lovett, J. C., Marquet, P. A., Merow, C., Midgley, G., Morueta-Holme, N.,…McGill, B. J. (2019). The commonness of rarity: Global and future distribution of rarity across land plants. *Science Advances*, *5*, eaaz0414.

Fajgenblat, M., Wijns, R., De Knijf, G., Stoks, R., Lemmens, P., Herremans, M., Vanormelingen, P., Neyens, T., & De Meester, L. (2025). Leveraging Massive Opportunistically Collected Datasets to Study Species Communities in Space and Time. *Ecol Lett*, *28*(3), e70094. https://doi.org/10.1111/ele.70094

Falaschi, M., Lo Parrino, E., Manenti, R., & Ficetola, G. F. (2025). Differences in estimates of extinction risk between occupancy and abundance data. *Conservation Biology*, *39*(4). https://doi.org/10.1111/cobi.70020

Fletcher, R. J., Green, R. E., Bladon, E. K., Atkinson, P. W., Phalan, B. T., Williams, D., Visconti, P., & Balmford, A. (2025). Beyond Species Richness for Biological Conservation. *Conservation Letters*, *18*(4). https://doi.org/10.1111/conl.13124

Fraisl, D., Hager, G., Bedessem, B., Gold, M., Hsing, P.-Y., Danielsen, F., Hitchcock, C. B., Hulbert, J. M., Piera, J., Spiers, H., Thiel, M., & Haklay, M. (2022). Citizen science in environmental and ecological sciences. *Nature Reviews Methods Primers*, *2*(1). https://doi.org/10.1038/s43586-022-00144-4

Freeman, S. N., Isaac, N. J. B., Besbeas, P., Dennis, E. B., & Morgan, B. J. T. (2020). A Generic Method for Estimating and Smoothing Multispecies Biodiversity Indicators Using Intermittent Data. *Journal of Agricultural, Biological and Environmental Statistics*, *26*(1), 71–89. https://doi.org/10.1007/s13253-020-00410-6

Gregory, R. (1998). An Intraspecific Model of Species' Expansion, Linking Abundance and Distribution. *Ecography*, *21*, 92–96.

Gregory, R. D., & van Strien, A. (2010). Wild bird indicators: using composite population trends of birds as measures of environmental health. *Ornithological Science*, *9*, 3–22.

Gregory, R. D., van Strien, A., Vorisek, P., Gmelig Meyling, A. W., Noble, D. G., Foppen, R. P., & Gibbons, D. W. (2005). Developing indicators for European birds. *Philos Trans R Soc Lond B Biol Sci*, *360*(1454), 269–288. https://doi.org/10.1098/rstb.2004.1602

Gullett, P. R., Leslie, C., Mason, R., Ratcliffe, P., Sargent, I., Beck, A., Cameron, T., Cowie, N. R., Hetherington, D., MacDonell, T., Moat, T., Moore, P., Teuten, E., & Hancock, M. H. (2023). Woodland expansion in the presence of deer: 30 years of evidence from the Cairngorms Connect landscape restoration partnership. *Journal of Applied Ecology*, *60*(11), 2298–2308. https://doi.org/10.1111/1365-2664.14501

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, *342*(6160), 850–853. https://doi.org/10.1126/science.1244693

Hartig, F., Abrego, N., Bush, A., Chase, J. M., Guillera-Arroita, G., Leibold, M. A., Ovaskainen, O., Pellissier, L., Pichler, M., Poggiato, G., Pollock, L., Si-Moussi, S., Thuiller, W., Viana, D. S., Warton, D. I., Zurell, D., & Yu, D. W. (2024). Novel community data in ecology-properties and prospects. *Trends in Ecology & Evolution*, *39*(3), 280–293. https://doi.org/10.1016/j.tree.2023.09.017

Hillebrand, H., Blasius, B., Borer, E. T., Chase, J. M., Downing, J. A., Eriksson, B. K., Filstrup, C. T., Harpole, W. S., Hodapp, D., Larsen, S., Lewandowska, A. M., Seabloom, E. W., Van de Waal, D. B., Ryabov, A. B., & Cadotte, M. (2018). Biodiversity change is uncoupled from species richness trends: Consequences for conservation and monitoring. *Journal of Applied Ecology*, *55*(1), 169–184. https://doi.org/10.1111/1365-2664.12959

Hoefer, S., Allen-Ankins, S., McKnight, D. T., Nordberg, E. J., & Schwarzkopf, L. (2025). Sensors versus surveyors: Comparing passive acoustic monitoring, camera trapping and observer-based monitoring for terrestrial mammals. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210x.70169

Isaac, N. J. B., Jarzyna, M. A., Keil, P., Dambly, L. I., Boersch-Supan, P. H., Browning, E., Freeman, S. N., Golding, N., Guillera-Arroita, G., Henrys, P. A., Jarvis, S., Lahoz-Monfort, J., Pagel, J., Pescott, O. L., Schmucki, R., Simmonds, E. G., & O'Hara, R. B. (2020). Data Integration for Large-Scale Models of Species Distributions. *Trends in Ecology & Evolution*, *35*(1), 56–67. https://doi.org/10.1016/j.tree.2019.08.006

Jarrett, D., & Willis, S. G. (2024). Acoustic detection rate can outperform traditional survey approaches in estimating relative densities of breeding waders. *Ibis*, *167*(2), 562–574. https://doi.org/10.1111/ibi.13375

JNCC. (2024). *Status of pollinating insects*. https://jncc.gov.uk/our-work/ukbi-pollinating-insects/

Johnston, A., Matechou, E., & Dennis, E. B. (2022). Outstanding challenges and future directions for biodiversity monitoring using citizen science data. *Methods in Ecology and Evolution*, *14*(1), 103–116. https://doi.org/10.1111/2041-210x.13834

Kacic, P., Thonfeld, F., Gessner, U., & Kuenzer, C. (2023). Forest Structure Characterization in Germany: Novel Products and Analysis Based on GEDI, Sentinel-1 and Sentinel-2 Data. *Remote Sensing*, *15*(8). https://doi.org/10.3390/rs15081969

Kissling, W. D., Ahumada, J. A., Bowser, A., Fernandez, M., Fernandez, N., Garcia, E. A., Guralnick, R. P., Isaac, N. J. B., Kelling, S., Los, W., McRae, L., Mihoub, J. B., Obst, M., Santamaria, M., Skidmore, A. K., Williams, K. J., Agosti, D., Amariles, D., Arvanitidis, C.,…Hardisty, A. R. (2018). Building essential biodiversity variables (EBVs) of species distribution and abundance at a global scale. *Biol Rev Camb Philos Soc*, *93*(1), 600–625. https://doi.org/10.1111/brv.12359

Kitzes, J., Blake, R., Bombaci, S., Chapman, M., Duran, S. M., Huang, T., Joseph, M. B., Lapp, S., Marconi, S., Oestreich, W. K., Rhinehart, T. A., Schweiger, A. K., Song, Y., Surasinghe, T., Yang, D., & Yule, K. (2021). Expanding NEON biodiversity surveys with new instrumentation and machine learning approaches. *Ecosphere*, *12*(11). https://doi.org/10.1002/ecs2.3795

Knight, K. B., Comer, P. J., Pickard, B. R., Gordon, D. R., & Toombs, T. (2021). Including Condition into Ecological Maps Changes Everything—A Study of Ecological Condition in the Conterminous United States. *Land*, *10*(11). https://doi.org/10.3390/land10111145

Lamb, E. G., Bayne, E., Holloway, G., Schieck, J., Boutin, S., Herbers, J., & Haughland, D. L. (2009). Indices for monitoring biodiversity change: Are some more effective than others? *Ecological Indicators*, *9*(3), 432–444. https://doi.org/10.1016/j.ecolind.2008.06.001

Lawley, V., Lewis, M., Clarke, K., & Ostendorf, B. (2016). Site-based and remote sensing methods for monitoring indicators of vegetation condition: An Australian review. *Ecological Indicators*, *60*, 1273–1283. https://doi.org/10.1016/j.ecolind.2015.03.021

Lengyel, S., Kosztyi, B., Schmeller, D. S., Henry, P.-Y., Kotarac, M., Lin, Y.-P., & Henle, K. (2018). Evaluating and benchmarking biodiversity monitoring: Metadata-based indicators for sampling design, sampling effort and data analysis. *Ecological Indicators*, *85*, 624–633. https://doi.org/10.1016/j.ecolind.2017.11.012

Lohr, S. L. (2021). *Sampling: Design and Analysis* (3 ed.). CRC Press.

Mancini, F., Cooke, R., Woodcock, B. A., Greenop, A., Johnson, A. C., & Isaac, N. J. B. (2023). Invertebrate biodiversity continues to decline in cropland. *Proceedings of the Royal Society B: Biological Sciences*, *290*(2000). https://doi.org/10.1098/rspb.2023.0897

Manes, F., Ricotta, C., Salvatori, E., Bajocco, S., & Blasi, C. (2010). A multiscale analysis of canopy structure in Fagus sylvatica L. and Quercus cerris L. old-growth forests in the Cilento and Vallo di Diano National Park. *Plant Biosystems*, *144*(1), 202–210. https://doi.org/10.1080/11263500903560801

Marston, C. G., O'Neil, A. W., Morton, R. D., Wood, C. M., & Rowland, C. S. (2023). LCM2021 – the UK Land Cover Map 2021. *Earth System Science Data*, *15*(10), 4631–4649. https://doi.org/10.5194/essd-15-4631-2023

Massimino, D., Baillie, S. R., Balmer, D. E., Bashford, R. I., Gregory, R. D., Harris, S. J., Heywood, J. J. N., Kelly, L. A., Noble, D. G., Pearce-Higgins, J. W., Raven, M. J., Risely, K., Woodcock, P., Wotton, S. R., & Gillings, S. (2025). The Breeding Bird Survey of the United Kingdom. *Global Ecology and Biogeography*, *34*(1). https://doi.org/10.1111/geb.13943

Matas-Granados, L., Pizarro, M., Cayuela, L., Domingo, D., Gómez, D., & García, M. B. (2022). Long-term monitoring of NDVI changes by remote sensing to assess the vulnerability of threatened plants. *Biological Conservation*, *265*. https://doi.org/10.1016/j.biocon.2021.109428

Matthies, D., Bräuer, I., Maibom, W., & Tscharntke, T. (2004). Population size and the risk of local extinction: empirical evidence from rare plants. *Oikos*, *105*(3), 481–488. https://doi.org/10.1111/j.0030-1299.2004.12800.x

McVittie, A., Cole, L., McCarthy, J., Fisher, H., & Rudman, H. (2023). *Research into Approaches to Measuring Biodiversity in Scotland*.

Nakagawa, S., Cornwell, W. K., & Callaghan, C. T. (2025). Decoupling both local and global abundance from global range size, challenging the abundance-occupancy relationship in birds. *Elife*, *13*. https://doi.org/10.7554/eLife.95857

Ockendon, N., Gullett, P. R., Hancock, M. H., Noble, D., Shaw, T., & Thomas, D. H. L. (2026). A framework for monitoring ecosystem restoration at landscape scale. *Conservation Science and Practice*, *8*(2), e70214. https://doi.org/10.1111/csp2.70214

OEP. (2025a). *Review of implementation of laws for terrestrial and freshwater protected sites in England*.

OEP. (2025b). *Review of implementation of laws for terrestrial and freshwater protected sites in Northern Ireland*.

Outhwaite, C. L., Gregory, R. D., Chandler, R. E., Collen, B., & Isaac, N. J. B. (2020). Complex long-term biodiversity change among invertebrates, bryophytes and lichens. *Nat Ecol Evol*, *4*(3), 384–392. https://doi.org/10.1038/s41559-020-1111-z

Outhwaite, C. L., Powney, G. D., August, T. A., Chandler, R. E., Rorke, S., Pescott, O. L., Harvey, M., Roy, H. E., Fox, R., Roy, D. B., Alexander, K., Ball, S., Bantock, T., Barber, T., Beckmann, B. C., Cook, T., Flanagan, J., Fowles, A., Hammond, P.,…Isaac, N. J. B. (2019). Annual estimates of occupancy for bryophytes, lichens and invertebrates in the UK, 1970–2015. *Scientific Data*, *6*(1). https://doi.org/10.1038/s41597-019-0269-1

Pereira, H. M., Ferrier, S., Walters, M., Geller, G. N., Jongman, R. H. G., Scholes, R. J., Bruford, M. W., Brummitt, N., Butchart, S. H., Cardoso, A. C., Coops, N. C., Dulloo, E., Faith, D. P., Freyhof, J., Gregory, R. D., Heip, C., Höft, R., Hurtt, G., Jetz, W.,…Wegmann, M. (2013). Essential Biodiversity Variables. *Science*, *339*, 277–278. https://doi.org/10.1126/science.1229931

Perino, A., Pereira, H. M., Felipe-Lucia, M., Kim, H., Kühl, H. S., Marselle, M. R., Meya, J. N., Meyer, C., Navarro, L. M., van Klink, R., Albert, G., Barratt, C. D., Bruelheide, H., Cao, Y., Chamoin, A., Darbi, M., Dornelas, M., Eisenhauer, N., Essl, F.,…Bonn, A. (2021). Biodiversity post-2020: Closing the gap between global targets and national-level implementation. *Conservation Letters*, *15*(2). https://doi.org/10.1111/conl.12848

Proença, V., Martin, L. J., Pereira, H. M., Fernandez, M., McRae, L., Belnap, J., Böhm, M., Brummitt, N., García-Moreno, J., Gregory, R. D., Honrado, J. P., Jürgens, N., Opige, M., Schmeller, D. S., Tiago, P., & van Swaay, C. A. M. (2017). Global biodiversity monitoring: From data sources to

Essential Biodiversity Variables. *Biological Conservation*, *213*, 256–263. https://doi.org/10.1016/j.biocon.2016.07.014

R Core Team. (2024). *R: A language and environment for statistical computing, https://www.R-project.org/*. In R Foundation for Statistical Computing.

Rao, J. N. K., & Mollina, I. (2015). *Small Area Estimation*. John Wiley.

Roberts, N. J. (2011). Investigation into survey techniques of large mammals: surveyor competence and camera-trapping vs. transect-sampling. *Bioscience Horizons*, *4*, 40–49. https://doi.org/10.1093/biohorizons/hzr006

Roe, P., Eichinski, P., Fuller, R. A., McDonald, P. G., Schwarzkopf, L., Towsey, M., Truskinger, A., Tucker, D., & Watson, D. M. (2021). The Australian Acoustic Observatory. *Methods in Ecology and Evolution*, *12*(10), 1802–1808. https://doi.org/10.1111/2041-210x.13660

Rooney, B. (2025). SNAPSHOT USA 2019–2023: The First Five Years of Data From a Coordinated Camera Trap Survey of the United States. *Global Ecology and Biogeography*.

Rowland, C. S., Marston, C. G., Morton, R. D., & O'Neil, A. W. (2020). Land Cover Change 1990-2015 (25m raster, GB). In: NERC Environmental Information Data Centre.

Schmeller, D. S., Julliard, R., Bellingham, P. J., Böhm, M., Brummitt, N., Chiarucci, A., Couvet, D., Elmendorf, S., Forsyth, D. M., Moreno, J. G., Gregory, R. D., Magnusson, W. E., Martin, L. J., McGeoch, M. A., Mihoub, J.-B., Pereira, H. M., Proença, V., van Swaay, C. A. M., Yahara, T., & Belnap, J. (2015). Towards a global terrestrial species monitoring program. *Journal for Nature Conservation*, *25*, 51–57. https://doi.org/10.1016/j.jnc.2015.03.003

Seaton, F. M., Jarvis, S. G., & Henrys, P. A. (2024). Spatio-temporal data integration for species distribution modelling in R-INLA. *Methods in Ecology and Evolution*, *15*(7), 1221–1232. https://doi.org/10.1111/2041-210x.14356

Simberloff, D. (1998). Flagships, umbrellas, and keystones: Is single-species management passé in the landscape era? *Biological Conservation*, *83*(3), 247–257. https://doi.org/10.1016/s0006-3207(97)00081-5

Stephenson, P. J. (2020). Technological advances in biodiversity monitoring: applicability, opportunities and challenges. *Current Opinion in Environmental Sustainability*, *45*, 36–41. https://doi.org/10.1016/j.cosust.2020.08.005

Stephenson, P. J., Londoño-Murcia, M. C., Borges, P. A. V., Claassens, L., Frisch-Nwakanma, H., Ling, N., McMullan-Fisher, S., Meeuwig, J. J., Unter, K. M. M., Walls, J. L., Burfield, I. J., do Carmo Vieira Correa, D., Geller, G. N., Montenegro Paredes, I., Mubalama, L. K., Ntiamoa-Baidu, Y., Roesler, I., Rovero, F., Sharma, Y. P.,…Fumagalli, L. (2022). Measuring the Impact of Conservation: The Growing Importance of Monitoring Fauna, Flora and Funga. *Diversity*, *14*(10). https://doi.org/10.3390/d14100824

Tebbs, E., Rowland, C., Smart, S., Maskell, L., & Norton, L. (2017). Regional-Scale High Spatial Resolution Mapping of Aboveground Net Primary Productivity (ANPP) from Field Survey and Landsat Data: A Case Study for the Country of Wales. *Remote Sensing*, *9*(8). https://doi.org/10.3390/rs9080801

Teixeira, D., Roe, P., van Rensburg, B. J., Linke, S., McDonald, P. G., Tucker, D., & Fuller, S. (2024). Effective ecological monitoring using passive acoustic sensors: Recommendations for conservation practitioners. *Conservation Science and Practice*, *6*(6). https://doi.org/10.1111/csp2.13132

van Swaay, C. A. M., Nowicki, P., Settele, J., & van Strien, A. J. (2008). Butterfly monitoring in Europe: methods, applications and perspectives. *Biodiversity and Conservation*, *17*(14), 3455–3469. https://doi.org/10.1007/s10531-008-9491-4

Watts, K., Whytock, R. C., Park, K. J., Fuentes-Montemayor, E., Macgregor, N. A., Duffield, S., & McGowan, P. J. K. (2020). Ecological time lags and the journey towards conservation success. *Nat Ecol Evol*, *4*(3), 304–311. https://doi.org/10.1038/s41559-019-1087-8

Yorkshire Wildlife Trust. (2024). *State of Yorkshire's Nature*.