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Scoping the use of predictive models to address priority questions concerning terrestrial biodiversity

Plummer, K.E.[1, 2], Powney, G.D.[3], Isaac, N.J.B.[3] & Siriwardena, G.M.[1]

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For further information please contact:

Joint Nature Conservation Committee
Monkstone House
City Road
Peterborough PE1 1JY
www.jncc.gov.uk

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Affiliation:

[1] British Trust for Ornithology, The Nunnery, Thetford, Norfolk, IP24 2PU, UK
[2] Centre for Ecology and Conservation, College of Life and Environmental Sciences, University of Exeter, Penryn Campus, Cornwall, TR10 9FE, UK
[3] NERC Centre for Ecology & Hydrology, Crowmarsh Gifford, Wallingford, OX10 8BB UK

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1 Background

Rapid environmental change caused by anthropogenic activities has a major influence on the state of natural ecosystems, impacting the biodiversity and human societies that depend on them (Sih *et al.* 2011). Determining the likely future impacts of environmental changes, and how to manage them, can be greatly enhanced using modelling approaches able to predict future ecosystem states and biodiversity patterns (Evans *et al.* 2013; Thaxter *et al.* in prep.).

A recent review by Thaxter *et al.* (in prep.) has evaluated the advantages and disadvantages of applying various predictive modelling approaches to the kinds of data produced by terrestrial biodiversity surveillance schemes (hereafter, ‘scheme data’). The report concluded that the suitability and effectiveness of each of these approaches is highly influenced by the types of data available, both in terms of the model’s response (e.g. occurrence or abundance) and predictor variables (in prep.). Therefore, to produce robust predictions that can support environmental decision-making, careful consideration is needed to identify the most appropriate modelling approach to use given the data available.

Here, following on from the work of Thaxter *et al.* (in prep.), we scope the priorities and potential for informative predictive analyses of terrestrial biodiversity patterns. Specifically, we identify and describe 12 research priorities and broadly summarise the data requirements needed for addressing them using predictive modelling. Then, we develop a suite of prospective research scenarios relating to these priorities, and use Thaxter *et al*. (in prep.) to identify potential predictive modelling methods that could be applied. Finally, considering the likelihood of being able to meet the data requirements, we evaluate the overall, current feasibility of addressing each research scenario. Broad conclusions from this scoping exercise are discussed at the end.

2 Aim

To examine the feasibility of using predictive modelling approaches to address priority research areas for terrestrial biodiversity surveillance.

3 Methods for scoping the use of predictive models

3.1 Identification of the priority areas for predictive modelling

This scoping report focuses on priority research topics with the greatest potential to benefit from the use of predictive modelling techniques, developed from those identified by the Terrestrial Evidence Partnership of Partnerships (TEPoP) annual meeting in 2017.

TEPoP was created to facilitate collaboration and knowledge exchange among a key set of partners working in the field of terrestrial biodiversity surveillance and monitoring. It includes all schemes in the UK that are supported by JNCC, and therefore represents an expert knowledge base for the key issues facing UK biodiversity, as well as the majority of relevant biodiversity data sources. TEPoP came together in October 2017 to discuss the scenarios deemed to be of greatest priority when it comes to using terrestrial biodiversity data for predictive modelling. All organisations involved in the consultation are listed in **Table 1**.

Table 1. A list of the organisations that were consulted to identify the priorities for predictive modelling of UK terrestrial biodiversity

Organisations that make up the Terrestrial Evidence Partnership of Partnerships (TEPoP)	
Represented at the consultation	
Bat Conservation Trust (BCT)	Natural Resources Wales (NRW)
Botanical Society of the British Isles (BSBI)	Plantlife
British Trust for Ornithology (BTO)	Royal Society for the Protection of Birds (RSPB)
Butterfly Conservation (BC)	Welsh Government (WG)
Centre for Ecology and Hydrology (CEH)	Wildfowl and Wetlands Trust (WWT)
Joint Nature Conservation Committee (JNCC)	
Not represented at the consultation	
Department of Agriculture, Environment and Rural Affairs (DAERA)	Department for Environment Food & Rural Affairs (DEFRA)
Forestry Commission	Scottish Government
Natural England (NE)	Scottish Natural Heritage (SNH)
Northern Ireland Environment Agency (NIEA)	

At the TEPoP meeting, a workshop was held to ask, specifically, 'What scenarios or interventions should be priorities for predictive modelling?'. The aim was to identify the needs of stakeholders for predictive models that can be applied to scheme data, with an initial focus on policy drivers. Attendees were divided into groups, avoiding multiple representatives of single organisations sitting in the same group, and ideas were noted by a facilitator, before being collated across groups and circulated among all TEPoP members for any further inputs after the meeting.

The meeting highlighted a number of cross-cutting themes, particularly the need to support national and international policy and decision-making. Some of the drivers on which predictive modelling should broadly focus were also identified, such as land management and land-use change, habitat quality, resource availability and generalised "pressures" of relevance to particular taxa or species. These have been distilled into 12 clearly defined, highly topical **Research Priorities** (listed in **Table 2**).

Table 2. The 12 Research Priorities identified as focal topics for exploring the application of predictive modelling to biodiversity data

Research Priorities
Land management and land-use change
1. Integrating biodiversity needs into **urban planning and development**
2. Evaluating the role of **landscape-scale restoration** in recovering biodiversity
3. Supporting well-planned **afforestation** to meet government targets
4. Evaluating options to improve **landscape connectivity**
5. Supporting **agri-environmental land management** decision-making post-Brexit
6. Understanding the risks and opportunities of **land abandonment** for biodiversity
7. The biodiversity impacts of changes to **sheep farming in the uplands**
8. Assessing the biodiversity consequences of management for **natural capital**
Environmental pressures
9. Mitigating and adapting to the impacts of **climate change**
10. Responding to the increasing challenge of **invasive non-native species**
11. Understanding the impacts of **air pollution** on terrestrial biodiversity
12. Estimating the threat of **chemical pollution** to biodiversity

3.2 Identifying potential data requirements and sources

The capacity to predict biodiversity responses to different environmental scenarios is limited by the availability of appropriate and reliable predictor data. Therefore, to be able to assess the feasibility of predicting biodiversity patterns, we first outlined the quantitative information that each Research Priority might require and then identified possible sources of data to meet these requirements. Information presented is based on existing knowledge, a limited search of relevant literature and online sources (given project time constraints) and consultation with BTO experts in each priority area.

3.3 Evaluating predictive modelling feasibility

Under each Research Priority, one to two **Research Scenarios** were identified, to provide examples of the specific questions one might hope to address using predictive modelling. A feasibility assessment was then conducted to evaluate the potential to address each Research Scenario. For each scenario, we have reviewed the specific data requirements and the applicable predictive modelling tools, based on Thaxter *et al*. (in prep.). The overall feasibility considered the availability and reliability of data to support the modelling approaches suggested. Estimates of species responses to environmental predictors are fundamental to all research scenarios: all predictive modelling is based on the extrapolation of some relationship between species status and the environmental factor of interest. In most of the proposals made in this report, these ‘response curves’ would be estimated from statistical models, but process-based models are also valuable in this respect. Such estimates can be derived from spatiotemporal models examining past environmental drivers of biodiversity change. In cases where the temporal aspect of the data is lacking, space-for-time approaches can be used to estimate species response to environmental predictors.

These approaches make different types of assumptions about the relationship between the current situation and the conditions under which predictions are being made.

4 Priority areas for predictive modelling

The 12 identified Research Priorities have largely been framed within a national and international policy context (see **Table 3** for full details). Most notably, they consider the application of predictive modelling in relation to key devolved government legislation and strategic policies concerning the natural environment and biodiversity across the four countries of the UK. Specifically, this includes the recent 25 Year Environment Plan (25YEP. HM Government 2018) in England, the Well-being of Future Generations Act 2015 (Welsh Government 2015b), the Environment (Wales) Act 2016 (Welsh Government 2016) and Natural Resources Policy Statement (Welsh Government 2015a) in Wales, the Scottish Biodiversity Strategy (Scottish Government 2004, Scottish Government 2013) and the Biodiversity Strategy for Northern Ireland (Department of Environment Northern Ireland 2015). Commonly, all devolved governments emphasise the need for biodiversity enhancement and ecosystem resilience through the sustainable management of natural resources. To this end, the Research Priorities are largely aimed at informing environmental decision-making in order to achieve these common goals, particularly in light of Brexit uncertainty.

The international policies of particular relevance to contextualising the Research Priorities include the UN Sustainable Development Goals (SDG), the Convention on Biological Diversity (CBD) and Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES).

Of note, the TEPoP group identified 'rewilding' as a priority topic, which broadly aims to restore self-regulating natural processes, reducing the need for human management. However, since there is no clear consensus on how rewilding should be put into practice (Nogués-Bravo *et al.* 2016), rather than addressing 'rewilding' *per se* as a Research Priority, we have focused more specifically on the importance of 'landscape-scale restoration' (Research Priority 2, **Table 2**) better to contextualise the scoping outcomes. For example, Chapter Two of the 25YEP specifically actions 'recovering and enhancing the beauty of landscapes' using several recognised rewilding approaches, including landscape-scale habitat restoration, creation and protection. Additionally, we have included a Research Priority centred around 'management for natural capital' (Research Priority 8, **Table 2**), which was not identified as a priority topic by TEPoP, but forms a cornerstone to the planned approaches to future environmental decision-making across the UK (Scottish Government 2013; HM Government 2018).

It is worthwhile acknowledging that there is a considerable degree of overlap between the Research Priorities, in terms of their intended outcomes and how they might be addressed in practice and, therefore, the predictive modelling applications that might be applied to inform them. For example, improvements in landscape connectivity (Research Priority 4) are likely to incorporate aspects of landscape-scale restoration (Research Priority 2) and afforestation (Research Priority 3), with knock-on consequences for climate change mitigation (Research Priority 9) and on invasive non-native species (INNS) spread (Research Priority 10). We have highlighted some of these cross-cutting themes within the Research Priority descriptions in **Table 3**.

While the focus of this scoping report is on terrestrial biodiversity, we note that some of the Research Priorities are not only relevant to the terrestrial environment and, by their nature, they will involve the freshwater environment as well (e.g. landscape restoration and INNS invasion pathways).

Table 3. Details of the 12 Research Priority topics (Table 2) that are expected to benefit from effective predictive modelling.

Research Priority topic	Further details	Predictive modelling application
1. Integrating biodiversity needs into **urban planning and development**	Urban expansion and densification are essential to provide housing, business and infrastructure needs in the UK, but they must be balanced with the commitment to halt biodiversity loss through sustainable land management (CBD & UNEP 2011; JNCC & DEFRA 2012). To achieve this, there is a drive to embed Biodiversity Net Gains approaches into development in the UK and strengthen standards for green infrastructure (Baker *et al.* 2019). For example, in England, the National Planning Policy Framework has recently been revised to align more closely with the 25YEP (Department for Communities and Local Government 2018b) and in July 2019, after public consultation, Defra proposed changes to the Environment Bill to make it mandatory that new developments achieve biodiversity net gains (Department for Environment Food and Rural Affairs 2018a: Department for Environment Food and Rural Affairs 2019). There are similar levels of support for the inclusion of green infrastructure and BNG approaches in planning across the UK (Baker *et al.* 2019).	• Reliable estimates of the biodiversity impact of urban development are greatly needed to support decision-making, locally and nationally, in order to achieve these ambitious targets. • Predictive modelling approaches could be especially valuable in determining likely biodiversity responses to new development proposals, in designing solutions to minimise biodiversity loss, in creating biodiversity-friendly urban landscapes and in improving the broader delivery of ecosystem service benefits.
2. Evaluating the role of **landscape-scale restoration** in recovering biodiversity	The over-arching goal of environmental policy and strategic planning throughout the UK is to leave the environment in a better condition for the next generation. For example, to accomplish this in England, the 25YEP proposes the development of a 'Nature Recovery Network' to protect and restore wildlife, while also having the potential to provide additional economic and societal benefits (HM Government 2018). Key objectives of the proposed Nature Recovery Network include restoring/ creating ecologically valuable habitats, such as woodland (see Research Priority 3) and grassland and restoring 75% of UK protected sites to 'favourable condition'. The importance of habitat restoration is emphasised throughout the UK as a means to improve the status of threatened and/or declining species groups such as butterflies and other pollinating insects, birds and bats, to restore habitat connectivity and ecological resilience and to provide robust ecosystem services (HM Government 2018; Scottish Government 2013; Welsh Government 2015a; Department of Environment Northern Ireland 2015).	• Using modelling to predict biodiversity responses to landscape restoration/ creation scenarios could be particularly valuable in supporting the delivery of a Nature Recovery Network that will 'provide the greatest opportunity for wildlife to flourish'. • Predictive modelling could also be used to assess how effective proposed habitat restoration projects aimed at improving the condition of protected areas are likely to be in supporting priority species and species groups.
3. Supporting well-planned **afforestation** to meet government targets	Increased tree planting, better woodland management and support for the forestry sector form key components of environmental policy across the four countries of the UK (Department of Environment Northern Ireland 2015; HM Government 2018; Welsh Government 2015a; Scottish Government 2013). For example, the 25YEP has reiterated existing targets for the planting of one million trees in urban areas by 2022, as well as endorsed proposals for a new Northern Forest, offering support to agroforestry and acknowledging plans for a new woodland creation scheme. It also outlines intentions to work with the timber industry, increasing commercial afforestation to meet growing demand.	• To support afforestation, predictive modelling could be used to identify areas which would benefit the most from tree planting and broadleaf woodland creation, by evaluating its predicted impacts on biodiversity and ecosystem services goals, as well as identifying the areas that should be excluded from afforestation. • Predictive modelling could also be applied to evaluate the consequences of different tree planting scenarios, particularly with respect to minimising potential detrimental effects of commercial afforestation on biodiversity.

Research Priority topic	Further details	Predictive modelling application
	Increasing tree numbers and woodland cover have the potential to provide new wildlife habitat, while also helping towards climate change mitigation, carbon offsetting and water management. However, commercial pine plantation and broadleaved woodland restoration/ creation will have very different impacts on wildlife. Although pine plantations have a high economic value, their biodiversity value is considerably lower than broadleaved woodland, while both could have negative influences on adjacent habitats.	
4. Evaluating options to improve **landscape connectivity**	Landscape connectivity is recognised as an integral aspect of ecosystem resilience throughout the UK, while England and Scotland have outlined specific plans to develop national ecological networks (Scottish Government 2013; Scottish Government 2015; HM Government 2018). The delivery of a Nature Recovery Network in England, for example (see also Research Priority 2), will be based on the recommendations of the Lawton Report, *Making Space for Nature* (Lawton *et al.* 2010), with the 25YEP stating specifically that 'recovering wildlife will require more habitat; in better condition; in bigger patches that are *more closely connected* (emphasis added)'. Notably, the Nature Recovery Network is expected to provide 500,000 hectares of additional wildlife habitat (see Research Priority 2) that will more effectively link existing protected sites and landscapes, as well as urban green and blue infrastructure. In Scotland the development of a 'National Ecological Network' via habitat restoration, creation and protection has been identified a strategic priority, though specific details about how and when this is expected to be delivered is unclear (Scottish Government 2015).	• To maximise habitat connectivity, predictive modelling could be used to identify optimal locations for habitat restoration/ creation (Isaac *et al.* 2018). Predictive modelling could also be especially valuable in providing an evidence-based evaluation of the potential delivery options for future projects aimed at improving landscape connectivity.
5. Supporting **agri-environmental land management** decision-making post-Brexit	UK agriculture has been governed by the EU's Common Agricultural Policy (CAP) for almost 50 years and has been criticised for encouraging farming practices that have negatively impacted the environment and farmland bird populations in particular. The UK government has set out plans for a new environmental land management system that will 'deliver more for the environment' by changing the distribution of subsidies to pay farmers for 'public goods' (e.g. via payment-by-results), thereby incentivising and rewarding land managers for enhancing the environment. To succeed in securing positive environmental outcomes from new UK agricultural policy, it is especially important that alternative options for its delivery and their potential biodiversity impacts are critically evaluated across all countries of the UK.	• Predictive modelling could be used to evaluate the potential consequences of different land management patterns given possible payment regimes (such as payment-by-results) and spatial targeting options (such as by region or by distribution of target species). Such models could be purely spatial, or they could be spatiotemporal to help to interpret longer-term impacts on species' population changes. • Specific modelling of the implications of policy options for multiple land-use and environmental targets in Wales is being conducted using an Integrated Modelling Platform within the Environmental & Rural Affairs Monitoring and Modelling Programme (ERAMMP) in 2019-20.
6. Understanding the risks and opportunities of **land**	Given Brexit uncertainty and the imminent changes to UK agricultural policy, marginal agricultural systems are at growing risk of abandonment, due to their reliance on subsidies and their low profitability. The loss of High Nature Value (HNV) agricultural land, in particular, is likely to negatively affect many open country, early successional species, whose conservation is	• The downstream consequences of vegetation succession on biodiversity due to land abandonment could be estimated using predictive modelling, therefore helping to identify species and locations of greatest conservation concern for targeted intervention,

Research Priority topic	Further details	Predictive modelling application
abandonment to biodiversity	dependent on well-maintained extensive farming. However, land abandonment also presents an opportunity for rewilding, ecosystem restoration and new landscape functions on previously environmentally poor agricultural lands.	such as directed subsidies under a new funding regime. • Models could also consider the effects of habitat change on biodiversity in areas where effects are predicted to occur, but ideally need data from the habitat type that will succeed the marginal farmland after abandonment.
7. The biodiversity impacts of changes to **sheep farming in the uplands**	Sustainably managed livestock grazing in the uplands helps to maintain a complex mosaic of habitats that are of significant biodiversity conservation value. However over-grazing and under-grazing can degrade vegetation structure and floristic diversity, with detrimental impacts to specialist upland species (Fuller 1996). Leaving the EU is likely to have a significant impact on sheep farming in the uplands. The sheep industry is heavily subsidised and has been shown to have various negative ecological implications, therefore it could be a prime target for change under agricultural policy reforms. Changes to the UK's trading relationships following Brexit could also contribute to the breakdown of the UK sheep industry, due to a likely deprecation of meat exports (Welsh Government 2018). Indeed, upland farmers are already being more cautious about livestock numbers for the year ahead.	• Predictive analyses could be used to model the biodiversity impacts of changes to sheep farming intensity expected to result from different Brexit trade deal scenarios. • It might also be possible to use future scenarios of the potential changes to upland habitats given the breakdown of the sheep industry, for example the restoration of semi-natural upland habitats, and predict potential responses of key species groups. • Similar analyses could also be extended to cattle, another important component of upland farmland, particularly on in-bye.
8. Assessing the biodiversity consequences of management for **natural capital**	Proposals for future land management in the UK have been strongly influenced by the recommendations of the Natural Capital Committee (NCC). Notably, the 25YEP sets out intentions to use a natural capital approach as a tool to 'help make key choices and long-term decisions' that will be good for the UK economy, generally, while also better supporting environmental enhancement. The NCC has considered the potential for planned investments in natural capital to deliver large economic returns, for example demonstrating a strong economic case for woodland planting around urban areas and peatland restoration (amongst others), with potential additional opportunities around farming and the urban environment. Measuring the contribution of wildlife as a natural capital asset *per se* is challenging. Therefore, it is perhaps likely that natural capital approaches will place greater focus on more easily measurable assets, such as woodland cover or air quality (see Research Priorities 3 & 11). However, land management aimed at natural capital gain could have additional wildlife benefits, particularly in the context of other pressures, such as climate change. There may, however, also be trade-offs between biodiversity conservation and wider ecosystem service delivery.	• It should be possible to understand the potential biodiversity impacts of managing land based on a natural capital framework using predictive modelling techniques. In particular, predictive models could be applied to quantify trade-offs, and mutual benefits, between wildlife and other natural capital assets. • However, it will only be possible to model trade-offs having already modelled each individual land-use scenario separately first.
9. Mitigating and adapting to the impacts of **climate change**	A key goal of environmental policy and strategies throughout the UK is to mitigate climate change, while adapting to reduce its impact. Land-use changes aimed at climate change mitigation (i.e. reducing greenhouse gas emissions), such as low-carbon farming practices, releasing agricultural land for alternative uses, peatland restoration and afforestation, also have the potential to have indirect implications for wildlife (both positive and	• Long-term terrestrial biodiversity data could be used to develop models predicting species' spatiotemporal responses to climate projections, helping to identify priority areas for new habitat creation, site protection or active management. Potentially, predictive modelling could also be used to evaluate species' responses to alternative climate adaptation

Research Priority topic	Further details	Predictive modelling application
	negative). But more specifically, the UK needs to implement adaptation approaches aimed directly at increasing the resilience of wildlife populations in the face of projected future climate change. Delivering a resilient ecological network of sites, that can improve species' persistence in a changing climate by enabling dispersal, for example, should be achievable following the 'bigger, better, more and joined' principles of Lawton's *Making Space for Nature* report (Isaac *et al.* 2018) (see also Research Priorities 2 & 4). But quantitative approaches are needed to underpin the creation of any such network, and to maximise its biodiversity (and other) benefits.	scenarios, thereby helping quantify the resilience of proposed landscape alterations to climate change. • It is potentially possible to develop detailed models for some exemplar species with good ecological knowledge of impacts and responses to mitigation. However, coarser-scale models, with less detailed ecological underpinning, could potentially be produced for a wider range of species.
10. Responding to the increasing challenge of **invasive non-native species**	Due to increases in international trade/ travel and climate shifts, invasive non-native species (INNS), including pests, are a growing threat to biosecurity with the potential to cause significant negative ecological and economic impacts. As such, the Invasive Non-Native Species Framework Strategy for Great Britain and the CBD advocate a hierarchical approach to tackling INNS, specifically focusing on prevention, followed by surveillance and rapid response, then control and eradication. Of course, to prioritise efforts in managing biological invasions, first, a good understanding of the risks posed by individual INNS is required. As such, the GB INNS Strategy calls for more robust risk assessments of the long-term impacts of INNS on vulnerable and protected species, sites and habitats.	• There are a number of ways by which predictive modelling could help to tackle INNS. For example, mitigation measures could be improved using predictions about where, and how, invasive species are likely to arrive, establish and spread. Also, predicting the possible population responses of native wildlife to INNS invasion could be especially valuable in determining the risk posed by individual INNS. Further, modelling could be used to predict the likely biodiversity consequences of successful INNS eradication. • Notably, however, every INNS is likely to behave differently, and to have different ecological and economic impacts. Therefore, predictive modelling on a case-by-case basis will have the greatest value. This could include models based on observed patterns of relative (change in) abundance or distribution, or on the mechanisms of likely impact (e.g. suppression of reproduction by competition, additive mortality, shading, spread of disease, *etc*.).
11. Understanding the impacts of **air pollution** on terrestrial biodiversity	Air pollution is the largest environmental health risk in the UK and is potentially responsible for widespread damage to natural ecosystem function and biodiversity. In particular, atmospheric nitrogen (N) deposition is predicted to be one of the greater drivers of global biodiversity loss over the coming century (Sala *et al.* 2000). The UK Government recently published the Clean Air Strategy 2019, outlining plans for dealing with all sources of air pollution. In particular, it is seeking to reduce ammonia emmisions, as a target for air quality improvements, using schemes such as the Farming Ammonia Reduction Grant scheme. Air pollutants – including Particulate Matter, Ozone, Nitrogen Oxides, Sulphur Dioxide and Carbon Monoxide – can have a direct impact on wildlife, causing respiratory distress, suppressing immune systems, impairing reproductive success and even reducing species diversity and richness (Lovett *et al.* 2009; Sanderfoot & Holloway 2017; Llacuna *et al.* 1993) Air pollutants also cause widespread losses of vascular plant, bryophyte and lichen species, changes to soil chemistry and habitat degradation via nutrient enrichment (eutrophication),	• Long-term terrestrial biodiversity surveillance data could be used to produce generalised models detailing the relationships between biodiversity and levels of air pollutants in the UK. These could then be used to predict future impacts, given projected changes in air pollutants, expected to occur in response to national and international legislation for reducing air pollution. • Note that identifying areas with high concentrations of air pollutants is likely to be particularly challenging because of atmospheric mixing over large spatial scales. It should also be acknowledged that if patterns in air pollutants are confounded with other spatiotemporal drivers, disentangling causal links with biodiversity change could be challenging.

Research Priority topic	Further details	Predictive modelling application
	acidification (lower pH), or direct damage (toxicity) processes. For example, ozone can reduce photosynthesis in plants, leading to a decline in growth (Reich & Amundson 1985). These habitat changes are likely to be indirectly impacting other taxonomic groups, such as invertebrates and birds, though evidence of the landscape-scale effects is currently lacking.	
12. Estimating the threat of **chemical pollution** to biodiversity	Chemical pollution in the environment (for example stemming from fertilizer, pesticide and pharmaceutical use) poses a significant threat to UK wildlife. In particular, point source pollution events have had major effects on freshwater ecosystems in the past (e.g. sewage in the River Thames, 2013), while there is also growing evidence of the damage to pollinator populations that has resulted from the use of neonicotinoid pesticides (Woodcock *et al.* 2016). In 2018, UK Government put in place new farming rules for water, aimed at reducing water pollution from agriculture. The 25YEP also emphasised plans to reduce the impact of chemicals via a new Chemicals Strategy. However, an understanding of the current and longer-term impacts of many chemical pollutants on biodiversity is lacking. Therefore, it is also unclear if these new policy initiates will reduce chemical pollution enough to produce positive wildlife outcomes.	• Predictive modelling could help to better understand the implications of chemical pollution for wildlife, and to identify reduction targets necessary to halt harmful effects. This, of course, assumes that potentially harmful chemical pollutants are known, and that associated data about their usage and/or their distribution within the environment is available.

5 Potential data requirements and sources

A summary of the potential data and ecological knowledge required to address each Research Priority is presented in **Table 4**, alongside some examples of possible sources of those data. This information has been summarised according to the different types of data needed to develop effective predictive models, specifically (1) biodiversity responses, (2) ecological knowledge to inform decisions about what needs to be accounted for within the model, (3) past/contemporary predictor data for model building, and (4) scenarios/projections over which predictions can be generated.

Biodiversity data are needed for all of the priorities listed and information on all taxa is potentially of interest, so scheme data sources are not listed in the table, and instead they are described in detail in **section 5.1** below. Their suitability for a given analysis will depend on the properties of the data set, such as whether it includes abundance or absence data (Thaxter *et al.* in prep.). Similarly, almost all biodiversity modelling will incorporate some form of land cover/land use and climate/weather data. Therefore, details of some potential sources of these data have been expanded upon in **section 5.2**.

It should be noted that the information presented in **Table 4** is based on existing knowledge, a limited search of relevant literature and online sources (given project time constraints) and consultation with BTO experts. It should not be considered an exhaustive list of all possible data sources.

To the best of our knowledge, all data sources listed are free to download or are available under licence and free of charge for non-commercial research purposes.

Table 4. Details of the data and ecological knowledge needed to address each Research Priority together with some sources of those data. Notably, this provides examples of the sorts of dataset and knowledge needed to construct meaningful models, although precise data requirements will depend on the specific research aims and chosen model structure.

Research Priority topic	Data type	Potential data requirements	Data sources
1. Integrating biodiversity needs into **urban planning and development**	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Quantitative understanding of the associations between biodiversity and urban landscape structure. • Information about biodiversity resource requirements, such as host plants, food sources or breeding habitats, at a taxon-appropriate scale.	• Modelled relationships between bird densities and fine-scale urban landscape structure (BTO in development (Plummer *et al.* in revision)) • Published literature and expert knowledge (e.g. Conservation Evidence)
	Model predictors	• Detailed land cover / land-use data, including the distributions of key biodiversity resource requirements identified above. • Information concerning known or anticipated urban pressures on biodiversity, such as artificial lighting, noise or predation. • Information about the population size and socio-economic demographics of UK urban areas.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Urban-specific LC/LU data sources → Urban Atlases: comparable LC/ LU data for 'Functional Urban Areas' in Europe for 2006 and 2012 → European Settlement Map → Imperviousness HRL: percentage/ change in sealed area → CDRC Dwelling Age: median house age per LSOA • Socio-demographics of UK urban areas → ONS Open Geography Portal: includes all boundary data for the UK including administrative, major towns & cities, the census, postcodes and NHS → OpenPopGrid: 10m resolution gridded population data → UK Gridded Population 2011: based on Census 2011 → UK population census (1971–2011) → PopChange: UK population change for 1971-2011
	Scenarios / projections	• Urban development requirements, plans and/or alternative design scenarios. • Projected human population and/or housing densities.	• Government prospectus for garden community delivery • Development proposals for new garden villages, e.g. Tresham garden village • Local authority planning application portals • Improving access to green spaces (Public Health England): Metrics covering the public distance to green space standards, built on Natural England's Access to Natural Greenspace Standard (ANGSt) • World Urbanisation Prospects: population projections until 2050

Research Priority topic	Data type	Potential data requirements	Data sources
2. Evaluating the role of **landscape-scale restoration** in recovering biodiversity	**Biodiversity responses**	• Species abundance and/or species occurrence data for priority species and species groups.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Information of the habitat requirements of priority species and species groups. • Quantitative understanding of ecological network requirements, informed by species' existing distribution, dispersal, home range size and ecological traits (for example).	• Published literature and expert knowledge (e.g. Conservation Evidence)
	Model predictors	• Data on the location and condition of habitats prior to intervention in order to aid predictions of where best to focus restoration of existing habitats or creation of new habitats. • Data on the nature and locations of contemporary habitat types that are expected to result from habitat restoration/ creation. • Information about designated UK protected areas, including their boundaries, 'condition', management regimes and biodiversity inventories. • Measures of weather/climate variability to reduce risk of confounding covariation.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • LC/LU data sources with a more specific focus on potential restoration habitats → Priority Habitat Inventory (England): spatial dataset that describes the geographic extent and location of Natural Environment and Rural Communities Act (2006) Section 41 habitats of principal importance → Habitat Networks Priority Restoration (Combined Habitats) (England): spatial data for the Habitat Networks for 18 priority habitats, including locations for habitat creation and potential areas for restoration • Protected areas → World Database on Protected Areas (WDPA): global database including the spatial extent of terrestrial protected areas, plus additional details about designation and management → UK protected sites data: JNCC summary data and digital boundaries for all designated and candidate SACs and SPAs in the UK • Data derived from comprehensive weather and climate data sources (see section 5.2.2)
	Scenarios / projections	• Plausible scenarios for landscape-scale restoration projects, considering socio-economic as well as landscape constraints.	• Conservation and Enhancement Scheme (CES) Agreements (England): spatial data for SSSIs targeted and prioritised for funding by Natural England to enable the land to be managed to achieve favourable condition • Afforestation proposals (see Research Priority 3)
3.	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)

Research Priority topic	Data type	Potential data requirements	Data sources
Supporting well-planned **afforestation** to meet government targets	**Ecological knowledge**	• Relationships between different types of forest cover and both target and non-target biodiversity, considering both within forest patches and in the surrounding areas. • Information about extent (distance) to which negative impacts of woodland cover extend into open ground. • Dispersal and colonisation probabilities of woodland species reaching new woodland planting.	• Published literature and expert knowledge (e.g. Conservation Evidence)
	Model predictors	• Current woodland/tree locations, densities, age structures and tree species compositions. • Measures of weather/climate variability to reduce risk of confounding covariation.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Woodland-specific LC/LU data source → National Forest Inventory (NFI) woodland map: all forest and woodland area > 0.5 ha, including details about woodland type and new planting, updated annually → Woody Linear Features Framework: describes the distribution of boundaries of hedges and lines of trees in Great Britain → Native Woodland Survey of Scotland (NWSS): map of the location, extent, type and condition of all native woodlands in Scotland from 2006-2013 → Ancient Woodlands England: inventory of ancient woodland sites in England → Urban Atlases: includes a street trees layer → Global Forest Change 2000 – 2017 → Forests HRLs: including densities, forest and leaf types, density change for 2012-2015 → Forestry Commission datasets: spatial and non-spatial data including woodland grant maps, forest boundaries, performance indicators and timber statistics • Data derived from comprehensive weather and climate data sources (see section 5.2.2)
	Scenarios / projections	• Spatially explicit afforestation scenarios showing proposed tree species.	• The Northern Forest manifesto: details the Woodland Trust's proposal to deliver the Northern Forest • Woodland Trust planting grants: it might be possible to access the locations and details of funded large-scale planting projects • Woodland planting opportunity maps (BTO in development)

Research Priority topic	Data type	Potential data requirements	Data sources
4. Evaluating options to improve **landscape connectivity**	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Quantitative understanding of the associations between biodiversity and landscape connectivity. • Information on dispersal ecology and movement patterns of target taxa with respect to landscape structure.	• Published literature and expert knowledge (e.g. Conservation Evidence) • Existing models of functional connectivity for different species and species groups, e.g. Grafius *et al*. (2017)
	Model predictors	• Habitat/ land cover maps with sufficient resolution to reveal existing levels of connectivity. • Data on topography, major roads and other potential barriers.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Woody Linear Features Framework: describes the distribution of boundaries of hedges and lines of trees in Great Britain • OS MasterMap Highways Network: details spatial data for the whole road network in Britain
	Scenarios / projections	• Scenarios of future/intended connectivity using the same parameters.	
5. Supporting **agri-environmental land management** decision-making post-Brexit	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Quantitative understanding of the associations between biodiversity and AES management interventions. • Information about biodiversity resource requirements, such as host plants, food sources or breeding habitats, at a taxon-appropriate scale.	• Published literature and expert knowledge (e.g. Conservation Evidence) • Existing models of biodiversity – farmland associations
	Model predictors	• Detailed land cover / land-use data, including the distributions of key biodiversity resource requirements identified above. • Current/historical spatial data on relevant management interventions (e.g. AES options) matched to species abundance or presence data, or to community metrics.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Land management interventions → CAP Payments data: breakdown of subsidies paid by scheme or measure

Research Priority topic	Data type	Potential data requirements	Data sources
			→ Environmental Stewardship Scheme Agreements (England): polygon maps of AES holdings agreements → Environmental Stewardship Scheme Options (England): maps for AES options uptake → CEH Land Cover *plus*: Crops: up to date maps of the distributions of a broad range of crop types
	Scenarios / projections	• Spatially explicit future intervention scenarios.	• Payment by results trial data • Potentially, projections derived from the Environmental & Rural Affairs Monitoring and Modelling Programme (ERAMMP)
6. Understanding the risks and opportunities of **land abandonment** to biodiversity	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Knowledge of habitat types that will develop after abandonment. • Quantitative relationships between biodiversity/species indices and both existing and potential, post-abandonment, habitats. • Likely rates of ecological succession on abandoned land and potential for colonisation by mid-late successional species.	• Published literature and expert knowledge (e.g. Conservation Evidence) • Species abundance data from successional gradients across appropriate habitats (BTO research)
	Model predictors	• Locations of HNV/marginal farmland. • Data on the condition of habitats prior to land abandonment. • Data on the nature and locations of contemporary habitat types that are expected to result from habitat land abandonment (i.e. possible successional habitats. • Measures of weather/climate variability to reduce risk of confounding covariation.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1), for example LCMs could be used to identify land-uses associated with marginal farmland. • LC/LU data with a focus on marginal farmland → National HNV maps (e.g. Maskell *et al*. in press for Wales) → Agricultural output map (Scotland): A map detailing the average standard output of farms by parish • Possible successional habitats → Copernicus Ploughing Indicator 2015: concentrates on historic land cover features with the aim to indicate ploughing activities in preceding years. Data are at a 20m resolution and map the number of years since the last indication of ploughing, from 1-6. Potentially, this could be coupled with prior/later land cover data to map habitat changes in years after ‘abandonment’, though this would need to be heavily caveated.

Research Priority topic	Data type	Potential data requirements	Data sources
			• Data derived from comprehensive weather and climate data sources (see section 5.2.2)
	Scenarios / projections	• Predictions (from socio-economic data?) of potential abandonment sites.	
7. The biodiversity impacts of changes to **sheep farming in the uplands**	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Understanding of how habitats that will develop in relevant areas in which grazing intensity could change, particularly around rates of change in vegetation structure and succession. • Knowledge of how species and species groups are impacted by sheep farming and different stocking rates/ grassland conditions.	• Published literature and expert knowledge (e.g. Conservation Evidence)
	Model predictors	• Sheep farming locations and stocking densities. • Data on the condition of uplands habitats along a gradient of stocking densities.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Priority Habitat Inventory (England): spatial dataset that describes the geographic extent and location of Natural Environment and Rural Communities Act (2006) Section 41 habitats of principal importance • Livestock densities → Agricultural maps for Scotland: including livestock numbers per hectare by parish → Livestock numbers in England and the UK: annual statistics
	Scenarios / projections	• Scenarios of based on potential changes to the UK's trading relationships following Brexit. • Scenarios of the potential changes to stocking densities.	• 'Brexit and our land' consultation: includes scenario analysis outlining three potential post-Brexit trade scenarios and quantifying their potential impacts on sheep farming in Wales • Potentially, data collected and model projections derived from the Environmental & Rural Affairs Monitoring and Modelling Programme (ERAMMP), following on from the Glastir Monitoring and Evaluation Programme (GMEP)

Research Priority topic	Data type	Potential data requirements	Data sources
8. Assessing the biodiversity consequences of management for **natural capital**	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Understanding of land management practices aimed at delivering desirable ecosystem services benefits (e.g. enhanced air and water quality), including how these might influence habitat composition and configuration. Models linking the land management scenarios to species' distributions / abundance. • Note that natural capital value may depend on location, so analyses using data with different spatial resolutions may produce different results.	• Published literature and expert knowledge (e.g. Conservation Evidence) • Forestry Scheme data could help to deliver knowledge of plant species interactions with different types of provisional services
	Model predictors	• Contemporary data for the parameters on which scenarios are built. In particular, land cover will be required, but finer-resolution habitat data (such as woodland tree species composition) might also be needed. • Many of the same data requirements as other Research Priorities, particularly 1, 2, 3 and 5.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Many of the same data sources as other Research Priorities, particularly 1, 2, 3 and 5
	Scenarios / projections	• Spatially explicit land management scenarios for natural capital.	• Natural capital scenario maps developed by the Natural Capital Committee
9. Mitigating and adapting to the impacts of **climate change**	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Ideally, knowledge of ecological/demographic processes by which climate change impacts and mitigation benefits may be expected to operate.	• Published literature and expert knowledge (e.g. Conservation Evidence) • Existing models
	Model predictors	• National and international weather and climate observations.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Data derived from comprehensive weather and climate data sources (see section 5.2.2)

Research Priority topic	Data type	Potential data requirements	Data sources
		• Land cover / land use data representative of likely habitat composition expected under different degrees of climate change.	• Global climate data → WorldClim V2: global climate data → CliMond: global climatologies for bioclimatic modelling → CRU TS dataset: high resolution gridded time-series data
	Scenarios / projections	• National and international climate projections • Spatial data on potential mitigation and adaptation scenarios.	• H++ extreme climate change scenarios • UK Climate Projections: UK and global gridded climate projections • Forestry Statistics 2016: includes statistics on carbon in forests, the Woodland Carbon Code and public attitudes to climate change
10. Responding to the increasing challenge of **invasive non-native species**	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Identities of non-native species of concern. • Species habitat and climate requirements in their home and invaded ranges. • Details of invasion history outside of UK. • Data pertaining to species' requirements for the UK. • Distribution data for any native species likely to be negatively impacted. • Knowledge of likely impact pathways and quantitative data on, e.g. demographic variables involved (structural equation models). OR	• Published literature and expert knowledge (e.g. Conservation Evidence) • GB Non-native Species Secretariat (NNSS): information to support the INNS Strategy • UK Plant Health Risk Register: Information about pests and tree health biosecurity • Global Biodiversity Information Facility: data holdings for the distributions of millions of species occurrence records globally • Map of Life: assembles and integrates different sources of data describing species distributions worldwide
	Model predictors	• Data from current or past range overlaps to inform relationships between invasive and native for wider prediction. • National and international land cover / land use data. • National and international weather and climate observations.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Data derived from comprehensive weather and climate data sources (see section 5.2.2) • Global land cover data → Copernicus Global Land Service: biophysical variables describing the state, the dynamism and the disturbances of the terrestrial vegetation

Research Priority topic	Data type	Potential data requirements	Data sources
			→ Climate Change Initiative (CCI) Land Cover V2: 23-class land cover map and 300 m resolution • Global climate data → WorldClim V2: global climate data → CliMond: global climatologies for bioclimatic modelling
	Scenarios / projections	• Scenarios of possible invasion pathways. • Projects patterns of relative (change in) abundance or distribution of INNS, for example following increased spread/establishment or the undertaking of management interventions.	• Based on expert opinion and/or published data?
11. Understanding the impacts of **air pollution** on terrestrial biodiversity	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Co-located measures of fine-scale variation in air pollution with fine-scale biodiversity information. Potential for avian demographic data to help provide more of a mechanistic link to any air pollution impacts.	• Published literature and expert knowledge (e.g. Conservation Evidence) • UK air pollution information resources guide: Guide to Defra publicly available datasets • UK Research on The Eutrophication and Acidification of Terrestrial Ecosystems (UKREATE): collate data which provide evidence for damage or recovery in a range of terrestrial habitats due to nitrogen deposition • UK Critical Loads and Dynamic Modelling: assessing the habitats at risk from acidification and eutrophication
	Model predictors	• Atmospheric nitrogen deposition. • Air pollution observations. • Spatially explicit air pollution observations and projections with a sufficiently fine spatial resolution to identify variations at scales relevant to biodiversity monitoring, such as 1km or 10km squares, with demonstrable variance in values that might support analyses of effects. • Similarly co-located fine-scale measures of other potential predictor variables, including land cover and climate, to reduce risk of confounding covariation. Although this could be problematic if a lot of the variation in	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Data derived from comprehensive weather and climate data sources (see section 5.2.2) • Air pollution → UK Deposition Data: vegetation-specific 3-year average deposition data for nitrogen and sulphur from 2004 to 2013 → Modelled Air Quality (MAQ): air pollution data for every 1-km square in Britain annually since 2002; differences in the modelling methods between years mean it cannot be used to measure temporal change → Automatic Urban & Rural Monitoring Network (AURN): air pollution data from 223 sites (1973-present) → UK Air Information Resource (UK-AIR): includes forecasting, historical data, and a catalogue of UK air quality monitoring, modelling and emissions datasets

Research Priority topic	Data type	Potential data requirements	Data sources
		pollution levels is confounded with, for example, urban land cover.	
	Scenarios / projections	• Air pollution projections.	• UK Air Information Resource (UK-AIR): (as above) • Updated energy and emissions projections 2017: projections of UK energy demand and greenhouse gas emissions up to 2035
12. Estimating the threat of **chemical pollution** to biodiversity	**Biodiversity responses**	• Species abundance and/or species occurrence data.	• Derived from terrestrial monitoring (see section 5.1)
	Ecological knowledge	• Knowledge of how species/species groups respond to pollutant concentrations and the impacts on communities. • Understanding of water quality standards.	• Published literature and expert knowledge (e.g. Conservation Evidence) • Water Framework Directive (WFD) standards and classifications
	Model predictors	• Representative spatial data on pollutant concentrations in relevant habitats. • Data of past and contemporary water quality status. • Information about past pollution incidences. • Similarly co-located fine-scale measures of other potential predictor variables, including land cover and climate, to reduce risk of confounding covariation. Although this could be problematic if a lot of the variation in pollution levels is confounded with, for example, urban land cover.	• Data derived from comprehensive land cover / land use data sources (see section 5.2.1) • Data derived from comprehensive weather and climate data sources (see section 5.2.2) • Scottish Environment Protection Agency (SEPA): publishes data on pollutant releases and water condition, including the Scottish Pollutant Release Inventory • Chemical pollution → CEH Land Cover plus Fertilisers and Pesticides: static maps of recent fertilizer and pesticide use → Environment Agency (EA) Pollution Inventory: collated information on annual mass releases of specified substances → EA Pollution Incidents: dataset detailing category 1 (major) and 2 (significant) pollution incidents reported to the EA → NRW Environmental Pollution Incidents: details pollution incidents reported to NRW (national coverage) • WFD sources of current water quality status
	Scenarios / projections	• Scenarios for long-term change in ambient pollution levels and/or for point source/acute pollution events.	• Based on expert opinion and/or published data?

5.1 Biodiversity response data

There are many national surveillance schemes in the UK that can provide suitable biodiversity response data for predictive modelling across multiple taxa and species groups, including birds, bats, butterflies, moths, pollinators and plants. These schemes encompass a range a structured and unstructured monitoring data, either in the form of species abundance or species occurrence, and often over large spatial extents and long time-series. Consequently, they are incredibly valuable for assessing species responses to environmental change. The majority of these data are the result of the efforts of vast networks of dedicated volunteer recorders, and the long history of recording biodiversity in the UK, coupled with varying extents of coordination and sampling design involving multiple government and non-government organisations. Approaches for generating predictions from these varied data types, considering potential biases and predictive performance, have been well described (Johnston *et al.* 2013; Massimino *et al.* 2018; Isaac *et al.* 2014; Johnston *et al.* 2019). Details of many of the different TEPoP surveillance systems that could be used for predictive modelling are given below, organised by taxon.

5.1.1 Birds

The BTO conducts structured surveys, using standardised data collection protocols, to monitor long-term variation in the distributions and abundances of UK bird species.

Breeding Bird Survey (BBS)	
Partners	BTO, JNCC and RSPB
Species	All UK breeding birds, mammals
Coverage	UK
Timespan	1994 – present
Survey period	April – June
Survey type	Structured
Data outputs	Data are published as Official Statistics, contribute to UK Biodiversity Indicators and have been widely used to model the impacts of different environmental drivers on bird distributions and trends (Sullivan *et al.* 2015; Baker *et al.* 2012; Martay *et al.* 2017), including the projected impacts of climate change (Renwick *et al.* 2012).

The BBS is conducted annually within a random sample of 1km squares across the UK, representative of all broad habitat types and stratified by observer density, for the purposes of monitoring national breeding bird population changes. The addition of recording of some terrestrial mammals has also proven valuable in assessing abundance patterns, while alignment with the Wider Countryside Butterfly Survey (WCBS), within the broader UK Butterfly Monitoring Scheme, has increased data collection for butterfly communities (Massimino *et al.* 2018; Eglington *et al.* 2015).

Wetland Bird Survey (WeBS)	
Partners	BTO, JNCC, RSPB in association with WWT
Species	All UK non-breeding waterbirds
Coverage	UK
Timespan	1947 – present
Survey period	Monthly, principally during September – March
Survey type	Structured

Data outputs	Data are used to determine waterbird population status and trends and to assess the importance of wetland sites, with the outputs supporting international conservation commitments, forming Official Statistics, and contributing to UK Biodiversity Indicators.

WeBS monitors the abundance and distribution of all UK non-breeding waterbirds, providing the principal data for the conservation of waterbird populations and wetland habitats. WeBS predominantly covers coastal sites, although many of the species also use inland habitats, and there is also a large sample of inland waterbodies in the scheme. The scheme uses Core Counts at 2,800 wetland sites throughout the UK, where surveyors record the numbers of all waterbird species present in their defined count area (WeBS sector). Counts are nationally synchronised on a designated Sunday each month, and they are completed at high tide at coastal sites. Low Tide Counts are additionally undertaken on selected estuaries to identify key areas used during the low tide period. Approximately 220 waterbird species, races or populations are counted each year, with national trends produced for the 110 most numerous species.

Goose and Swan Monitoring Programme (GSMP)	
Partners	WWT, JNCC, SNH
Species	Geese and swans
Coverage	Varies from single sites to whole flyways
Timespan	1940s – present
Survey period	Varies by survey, but principally covering the winter period
Survey type	Structured, semi-structured, unstructured
Data outputs	Data contribute to national waterbird Official Statistics and UK Biodiversity Indicators, and are also used to support international conservation commitments and local environmental management.

The GSMP monitors the abundance, breeding success, survival and movements of the UK's native geese and migratory swans in the non-breeding season. GSMP encompasses a network of organisations, groups and individuals using bespoke surveys to accurately monitor goose and swan populations for which standard WeBS methods are unsuitable. To produce updated estimates of overall population size and breeding success, many GSMP surveys and censuses are carried out at a flyway scale, though some are more restricted in geographical extent and focus on particular regions or sites.

Avian Demographics Scheme (ADS)	
Partners	BTO, JNCC, NRW, NE, NIEA and SNH
Species	All UK birds
Coverage	UK
Timespan	1947 – present
Survey period	All year
Survey type	Semi-structured, unstructured
Data outputs	Data contribute to UK biodiversity indicators and are frequently used to model the potential mechanisms underlying broader population trends.

The ADS combine the Nest Record Scheme and the Bird Ringing Scheme to gather data on the productivity, survival and movements of UK birds. The Nest Record Scheme involves collection of standardised nesting information from *ad hoc* nest locations. The national Bird Ringing Scheme comprises three components: bird ringing at *ad hoc* locations, ringing at Constant Effort Sites (repeated trapping at a set location following standardised protocol), and more intensive scientific studies in the Retrapping Adults for Survival scheme. Reporting of dead recoveries of ringed birds subsequently forms an independent, but critical, component of information gathering from ringing.

Bird Atlas 2007-2011 (Balmer *et al.* 2013) provides comprehensive data of the distributions and abundances of all bird species in the UK, both in summer and in winter, based on fixed-effort surveys at a 2 × 2km tetrad resolution (nested within 10 × 10km grid squares). These data have recently been used to investigate the impacts of climate change and projected urban development on UK bird populations (Gillings *et al.* 2014; Gillings under revision).

5.1.2 Bats

National Bat Monitoring Programme (NBMP)	
Partners	BCT, JNCC and NRW
Species	All resident UK bat species
Coverage	UK
Timespan	1997 – present
Survey period	All seasons are incorporated, but exact survey period varies by survey type
Survey type	Structured, semi-structured
Data outputs	Data are routinely analysed to produce estimates of bat population status, change and distribution. Results are published as Official Statistics and contribute to UK Biodiversity Indicators.

The NBMP is a series of bat surveys conducted annually by volunteers in order to monitor the population changes of British bats. It currently covers approximately 2,000 sites per year and produces trends for 11 of the UK's 17 resident bat species at GB level. The scheme includes four core surveys (the Field Survey, Waterways Survey, Hibernation Survey and Roost Count), plus targeted surveys for barbastelle (Woodland Survey) and Nathusius' pipistrelle (National Nathusius' Pipistrelle Project) and an entry-level survey for volunteers to record bat presence and potential roosts at self-selected sites (Sunset/Sunrise Survey).

5.1.3 Butterflies

UK Butterfly Monitoring Scheme (UKBMS)	
Partners	BC, CEH, BTO and JNCC
Species	All 71 butterfly species that have been recorded in Britain and Ireland
Coverage	UK
Timespan	1976 – present
Survey period	April – September
Survey type	Structured, semi-structured
Data outputs	UKBMS data modelling approaches are well-described (Dennis *et al.* 2016; Dennis *et al.* 2013; Isaac *et al.* 2011; Dennis *et al.* 2017), and have been widely used to study impacts of climate- and habitat-related environmental change (Oliver *et al.* 2017; Oliver *et al.* 2010; Powney *et al.* 2011; Martay *et al.* 2017). Results are published as Official Statistics and contribute to UK Biodiversity Indicators.

The UKBMS monitors changes in the abundance and status of UK butterflies using three complementary survey methods: fixed-route transects (Pollard walks), the Wider Countryside Butterfly Survey (WCBS) and reduced effort surveys. Fixed butterfly transects have been walked weekly throughout summer at approximately 1,500 sites since 1976. Since 2009, the WCBS has been conducted two-three times per summer at approximately 800 additional (random stratified) 1km squares, in conjunction with the Breeding Bird Survey (BBS). Reduced effort surveys are used for rare, habitat-specialist species. These include timed counts of adults, single species transects and monitoring of egg numbers and larval nests.

5.1.4 Pollinators

UK Pollinator Monitoring Scheme (PoMS)	
Partners	Co-ordinated by CEH, funded by Defra, Welsh and Scottish Governments, JNCC and project partners (CEH, Bumblebee Conservation Trust, BC, BTO, Hymettus, University of Reading, University of Leeds)
Species	Bees, hoverflies and other flower-visiting insects
Coverage	England, Wales and Scotland
Timespan	2017 – present
Survey period	April – September
Survey type	Structured, semi-structured
Data outputs	Data will be used to derive metrics and/or indicators of pollinator population changes that can also be linked with contextual data on land-use, habitat and other environmental variables (Carvell *et al.* 2016).

The PoMS has recently been established as part of the broader UK Pollinator Monitoring and Research Partnership. It aims to provide structured data on the state of the UK's pollinator insects, particularly wild bees and hoverflies, and the role these play in supporting farming and wildlife. The PoMS is comprised of two surveys, Flower-Insect Timed (FIT) Counts and 1km Square Surveys. FIT Counts involve recording all insects (to a broad species group level) that land on a particular flower species within a 50cm survey square during a 10 minutes period. FIT Counts can be completed anywhere, but volunteers are encouraged to sample at one of 14 target flower species and to do repeated counts within the same season. For the 1km Square Survey, a network of 75 1km squares have been randomly allocated within cropped and non-cropped land for intensive systematic sampling of insects using water-filled pan traps. Five pan trap stations are located within each square and all insects captured over a six-hour period are identified, with the protocol repeated four times within a season.

5.1.5 Vascular plants

National Plant Monitoring Scheme (NPMS)	
Partners	BSBI, CEH, Plantlife and JNCC
Species	All vascular plant species
Coverage	UK
Timespan	2015 – present
Survey period	Summer
Survey type	Structured
Data outputs	A novel combined abundance/occupancy indicator based on NPMS data has been developed (Pescott *et al.* 2019a), and power analyses have indicated the future potential for NPMS to detect temporal changes in habitat quality (Pescott *et al.* 2019b).

The NPMS is a habitat-based plant survey conducted across a sample of random stratified 1km squares in order to monitor changes in plant abundance and diversity. Volunteer surveyors record the abundance of various plant 'indicator species' in at least five plots of differing habitats within their allocated square. A total of 28 predefined semi-natural habitat types are included, each with up to 30 associated (positively and negatively) indicator species. The survey can be completed at three different levels, defined by the number of species searched for per habitat, giving surveyors the option to report a subset of indicator species (Wildflower Level), all indicator species (Indicator Level) or every vascular plant species (Inventory Level) in their plots.

5.1.6 Biological Records Centre (BRC)

Scheme overview: BRC	
Partners	CEH, JNCC and NERC
Species	Numerous plant, invertebrate and vertebrate groups
Coverage	UK
Timespan	1964 – present
Survey period	Varies by survey type
Survey type	Structured, semi-structured, unstructured
Data outputs	Biological records are routinely analysed to address a host of ecological questions, ranging from assessing the impact of climate change on species phenology, to modelling potential environmental drivers of long-term change in species distributions. The wide range of species for which biological records are available enables users to ask questions related to specific subsets of taxa, for example threatened (priority), iconic or economically important species (e.g. pollinators).

The BRC works with over 80 taxonomic-group-specific recording schemes and societies, for example the UK Hoverfly Recording Scheme (HRS) and the Botanical Society of Britain & Ireland (BSBI). While finer-scale resolutions are available for some taxa, biological records tend to be analysed at the 1 x 1km or 10 x 10km gridded resolution. Recording intensity has varied through time, however the core period of recording for most taxonomic groups is from 1970s/1980s onwards. Given much of the distribution data were collected without a standardized protocol, several forms of bias (e.g. spatiotemporal variation in detectability) must be accounted for when modelling these data. Numerous methods have been developed to deal with the bias and limitations; we discuss these in Case Studies 2 and 3 below.

5.2 Predictor variable data

All biodiversity predictive modelling is likely to incorporate some form of land cover and/or climate data for the UK, alongside the other, more specific predictors described in **Table 4**. Therefore, there are a number of data sources that could be drawn upon when addressing any of the 12 Research Priorities. In the case of land cover/ land-use data, these include CEH land cover maps, Earth Observation data Copernicus Land Monitoring Service and OS MasterMap, while, for weather/climate data, these include the UK Met Office and the Climate, Hydrology and Ecology research Support System (CHESS). Given their broad relevance, we have provided a description of each of these, and some of the specific data products they include, below. Of course, choosing the most appropriate data source, specific data product and variable derivation approach will depend on the research question of interest. We have included further details of land cover/land-use and climate/weather data sources with particular relevance to the different Research Priorities in **Table 4**.

5.2.1 Land cover/ land-use (LC/LU) data sources

CEH Land Cover Maps (LCM): UK-wide land cover spatial data for 1990, 2000, 2007, 2015 in both vectorised and raster formats at a range of spatial resolutions (25 x 25m or 1 x 1km). They include 22 land cover classes based on UK Biodiversity Action Plan Broad Habitats. Consecutive LCMs are not suitable for measuring land cover changes, due to changes in land classifications between iterations, and therefore should not be used for modelling temporal changes in land cover. LCM habitat classes can be further refined using CEH's Land Cover *plus* spatial datasets for Crops (2015 onwards), Fertilisers (2010-2015 average) and Pesticides (2012-2016 average), and the Hydrology of Soil Types (HOST; UK-wide 1-km gridded data for 29 soil classes).

Copernicus Land Monitoring Service (CLMS): uses remote sensing technologies to produce geographical information on land cover, land-use, land cover-use changes over the years, vegetation state and the water cycle. CLMS is split into three components: Global (bio-geophysical features at mid and low spatial resolution), Pan-European (LC/LU and their changes) and Local (more detailed information for specific 'hotspots'). The Pan-European is probably of greatest broad relevance (with the potential to separate products at a UK GB and country level) and includes the following data products.

- CORINE Land Cover (CLC): includes 44 land classes for 1990, 2000, 2006, 2012, 2018 at 25ha / 100m resolution. Change layers (CLCC) are also available, which identify areas (>5ha area and >100m width) where land cover classes have changed between two consecutive maps.

- High Resolution Layers (HRL): more detailed information about status and change of five land cover themes – the level of sealed soil (imperviousness), tree cover density and forest type, grasslands, wetness and water, and small woody features – available at 20m and 100m resolutions. All themes include static maps for 2015, with additional years (and between-year changes) for the imperviousness and forest layers.

- European Settlement Map (ESM): a raster (2.5, 10 & 100m resolution) based on satellite imagery from 2012 differentiating between buildings, green and open spaces.

CLMS data are also used to underpin country-specific Living Map projects, which could offer a valuable source of dynamic habitat data for use in the development of predictive modelling.

OS MasterMap (OSMM): high resolution, highly detailed vectorised data for Great Britain that is updated regularly. The Topography Layer uses descriptive terms to differentiate between hundreds of LC/LU features, and also now includes 'Building Height Attributes' for visualising and analysing the built environment in 3D. The data are updated every six weeks and include details and timings of any LC/LU changes. Other OSMM data layers with additional detail about specific land cover types include the Highways Network, Greenspace and Water layers.

It is also worthwhile noting that some of the biodiversity monitoring schemes outlines in section 5.1 also collect habitat information alongside species recording. These schemes also offer the potential to collect additional field variables, or ground truth EO data, whilst undertaking biodiversity recording.

5.2.2 Weather and climate data sources

Met Office: maintains observational and projected data for the purposes of long-term monitoring of the UK's climate at different scales.

- UK and regional series: time-series (per month, season and year) for seven weather variables, including temperature and rainfall, for the UK, countries and regions.

- HadUK-Grid: high resolution (1 x 1km) gridded land surface observational climate data set for the UK from ca 1960 onwards (start differs between variables), interpolated from weather station data. Daily values are available for temperature and rainfall, with additional variables (e.g. days of ground frost, days of snow lying, wind speed, sunshine, max/min/average air temperature) also available per month, season and year. Data are also provided as long-term averages (1961-1990, 1981-2000) and at 12km, 25km, and 60km resolutions to facilitate comparison with UKCP18 climate projections.

- UK Climate Projections 2018 (UKCP18): various climate projections for the UK and globally up until 2100 covering a range of greenhouse gas emission scenarios and warming levels. Climate projections for the globe are provided at a 60km scale and for the UK at a 12km scale, with the UK data also downscaled to produce summarised data for regions, countries and the whole UK. Depending on the dataset used, projections are available for daily, monthly, seasonal, annual and 20/30-year means.

Climate, Hydrology and Ecology research Support System (CHESS): high resolution (1 x 1km) daily mean meteorological data on a number of important climate variables, including, but not limited to, temperature and rainfall (1962 onwards).

6 The feasibility of using predictive models to address research priorities

The feasibility assessment for each Research Scenario is given in **Table 5**. In each case, there are multiple analytical methods that could be used to generate predictions. We have summarised the general modelling approaches that are likely to be most suitable (**Table 5: 'potential modelling approach'**), based on Thaxter *et al.* (in prep.). In particular, we have focused on the following features when determining potential modelling approaches: data requirements, treatment of sample bias/ uncertainty and applicability for abundance data, distribution data, time-series modelling and/ or extrapolation (see Thaxter *et al.* in prep. Table 1). Note that definitive decisions about which method to employ (for example, whether to use abundance versus presence-only data, or to assess whole communities versus target species) will depend on the explicit aims, objectives and hypotheses under examination. Since we have not attempted to develop Research Scenarios to this degree of detail, it was inappropriate to identify specific response and predictor terms and, therefore, exact model types for their analysis here.

Table 5. Examples of some possible research scenarios for each Research Priority, with details of potential modelling approaches (based on Thaxter *et al.* in prep.) and an assessment of their overall feasibility. Research scenarios have been coloured by overall feasibility; orange = high/reasonably high, green = moderate, blue = low. The four scenarios given in bold have been expanded upon in the 'case studies' section below.

Research Priority	Example research scenario	Potential modelling approach †	Overall feasibility assessment
1. Integrating biodiversity needs into **urban planning and development**	**Estimating the effects of proposed garden village developments on bird communities (Case Study 1)**	• Use a regression framework (e.g. GLM, MARS, GAM, BH), since these are suitable for extrapolation of abundance data through space. Existing GLM models of bird-urban habitat relationships could be refined and used for prediction, or these could be refitted with Bayesian models (i.e. BH) for greater flexibility. • Alternatively, or to consider additional data sources and taxonomic groups, use joint species distribution models (JSDMs) to model multiple species' abundances hierarchically and then assess community-level patterns.	**High:** Models of bird-urban habitat relationships have already been developed and suitable scenario data are available. Analyses could also be applied to other taxa for which data are available. Note that, although JSDMs are a potentially powerful approach to studying whole community responses, their predictive ability has not been well-studied yet (Thaxter *et al.* in prep.). Therefore, a regression framework could be more effective, and easier and less time-consuming to implement.
2. Evaluating the role of **landscape-scale restoration** in recovering biodiversity	**Assessing pollinator responses to the restoration of wildflower-rich grassland, meadows and heathlands, in close proximity to urban and sub-urban environments (Case Study 2)**	• Use hierarchal dynamic occupancy models fitted within a Bayesian framework, since these are suitable for extrapolation of distribution data across time and space, This will allow drivers of site colonisation and extinction to be modelled explicitly, making greater use of spatiotemporal data, and ultimately have improved prediction accuracy (Guillera-Arroita 2017).	**High:** This analytical approach has been used successfully in the past to model pollinator responses to pesticides and crop cover, see Woodcock *et al*. (2016). Using suitable scenario data, it should be straightforward to apply these same methods within the context of predictive modelling.
	Assessing biodiversity responses to increasing the coverage, and status, of SSSIs (Case Study 3)	• Use hierarchal dynamic occupancy models fitted to opportunistic biological records within a Bayesian framework, since these are suitable for extrapolation of distribution data across time and space. • Use a GLM or BH regression approach to predict abundance changes through time and space.	**Reasonably high:** The analytical approach proposed is similar to that used in the past to successfully model opportunistic biological records (Woodcock *et al.* 2016). Predictive potential will rely on species showing sensitivity to SSSIs condition. However, given the number of drivers that influence species abundance and distribution it may be hard to detect genuine signals of SSSI condition.

Research Priority	Example research scenario	Potential modelling approach †	Overall feasibility assessment
3. Supporting well-planned **afforestation** to meet government targets	Evaluating the potential impacts of proposed woodland creation plans on the status of key wildlife groups	• Use a regression framework (e.g. GLM, MARS, GAM, BH), since these are suitable for extrapolation across time and space and are applicable to both abundance and distribution data. • Bayesian hierarchical methods (BH) might be most appropriate, as they will allow greater flexibility, e.g. the isolation of errors and uncertainty evaluation.	**Low:** Comprehensive data on woodland structure and distribution are available to support model development. However, producing reliable predictions could be challenging, due to the slow maturation of newly created woodlands – factors such as climate and species' population contexts are likely to be considerably different by the time that new forest patches are sufficiently mature to resemble forest patches that are used to build contemporary models.
4. Evaluating options to improve **landscape connectivity**	Understanding how increasing numbers of street trees (as proposed in the 25YEP) will influence the flow of birds through urban areas	• Use a GIS-based connectivity modelling approach, such as Circuitscape (McRae *et al.* 2013), to predict movement patterns of selected bird species under different street tree configurations.	**Moderate:** Circuit theory approaches have proved successful previously in modelling of urban landscape connectivity for birds, although predictive performance can be poor if models are not well-parameterised (Grafius *et al.* 2017). The availability of fine-scale empirical data and quantified species – habitat relationship gradients, necessary to support the selection of model parameters, will limit the potential to produce robust predictions to specific localities.
5. Supporting **agri-environmental land management** decision-making post-Brexit	Investigating the potential biodiversity outcomes of introducing a payments-by-results agri-environment land management system	• Use a regression framework (e.g. GLM, MARS, GAM, BH), since these are suitable for extrapolation across space and are applicable to both abundance and distribution data.	**Moderate:** Many interpretative analyses have been conducted, so the limits are likely to be in the availability of relevant scenario data and assumptions of transferability between current management and what would be produced by payment-by-results. Note that previous studies have found effects to be small and difficult to detect, so predictions are unlikely to suggest large changes (although scaling-up to a coarser resolution could improve detection of effects). New models of absolute abundance are likely to be needed, as opposed to existing analyses of growth rates.

Research Priority	Example research scenario	Potential modelling approach †	Overall feasibility assessment
6. Understanding the risks and opportunities of **land abandonment** to biodiversity	Assessing the biodiversity impacts of possible abandonment scenarios	• Use joint species distribution models (JSDMs) to model abundance or distribution of multiple species hierarchically and then assess community-level patterns.	**Low**: The timescale considered post-abandonment will also be a key assumption; predictions are likely to be more reliable over shorter timeframes. The availability of both socio-economic data (needed to develop likely abandonment scenarios) and valid assumptions about the habitats that will be created by abandonment are uncertain. Further, although JSDMs are a potentially powerful approach in this context, their predictive ability has not been well-studied yet and will therefore require close examination if used (Thaxter *et al.* in prep.).
7. The biodiversity impacts of changes to **sheep farming in the uplands**	Assessing the impacts of changes to sheep farming intensity following proposed agricultural/ trade policy reforms on target upland species	• Use a machine-learning approach to maximise the use of limited data for making predictions using presence-only data (e.g. ME).	**Low:** Only sample data on sheep numbers are currently available in national statistics, limiting the potential to parameterise models that can be used for prediction. Further, biodiversity monitoring of upland habitats tends to be sparse, and therefore addition data collection might be required to fill gaps.
8. Assessing the biodiversity consequences of management for **natural capital**	Evaluating the biodiversity trade-offs, and mutual benefits, associated with managing land for natural capital gain	• Use Bayesian hierarchical methods (BH) to extrapolate across time and space and allow for flexible species distribution and abundance modelling. • Alternatively, use machine-learning methods (e.g. CRT, RF, BT, BRT), which can be beneficial for modelling wildlife-habitat relationships as they are non-parametric and make no assumptions about the underlying relationship between the predictor variable of interest and the response.	**Moderate:** This will be dependent on the availability of suitable scenarios (land cover and other changes predicted under management for natural capital). Analyses could consider all taxa for which data are available but will be computationally demanding and time-consuming to complete. They will also need to be caveated heavily to account for uncertainty in land cover change.

Research Priority	Example research scenario	Potential modelling approach †	Overall feasibility assessment
9. Mitigating and adapting to the impacts of **climate change**	Estimating the effects of proposed climate change adaptation strategies on target taxa	• Use Bayesian hierarchical methods (BH) for the extrapolation of either species abundance or presence-only across time and space. • Spatially-explicit demographic modelling approaches could also be applied to predict the impacts of climate projections while incorporating dispersal information (Massimino *et al.* 2017).	**Moderate:** Given appropriate contemporary data on taxa of interest in the habitat types to be created and in response to management, habitat association models could readily be fitted. However, meaningful modelling of species' distribution shifts would ideally require consideration of dispersal and habitat constraints and will probably require prediction beyond the range of the data, so predictive performance would need evaluation.
10. Responding to the increasing challenge of **invasive non-native species**	Evaluating the habitat factors promoting the establishment of ring-necked parakeets	• Use regression trees, i.e. a data-driven machine-learning classification method (e.g. RF, BRT). These have been recommended for modelling abundance-habitat relationships because they optimise prediction quality out-of-sample, deal with concerns over skewed response data and can encompass complex response-predictor relationships (Thaxter *et al.* in prep.; Balmer *et al.* 2013).	**Moderate:** Suitable data exist or can be extracted from remote-sensed sources, but models will need to be fitted to identify how well the available data can characterize habitats, i.e. potential model quality.
	Estimating the likely impacts of rhododendron clearance on woodland birds/butterflies	• Use a regression framework (e.g. GLM, MARS, GAM, BH), since these are suitable for extrapolation across space and are applicable to both abundance and distribution data.	**Low:** The likelihood of being able to generate predictions will be dependent upon information on rhododendron cover. This may be a problem as it is nearly ubiquitous, but poorly recorded. Hence clearance may be easier to test than "natural" presence/absence. Sites will be individual woods, so spatially imprecise or grid-square-level data may not be useful.
11. Understanding the impacts of **air pollution** on terrestrial biodiversity	**Estimating changes in species abundance in response to projected**	• Use a regression framework to allow for time series modelling of both abundance and distribution (e.g. GLM, MARS, GAM, BH). In particular, GAMs would be most effective in modelling non-linear patterns in	**Reasonably high:** This would require substantial prior analysis to the relationships between different aspects of biodiversity and levels of air pollutants in the UK. Suitable air quality data should be available from Defra. It would also be dependent on appropriate

Research Priority	Example research scenario	Potential modelling approach †	Overall feasibility assessment
	changes in air pollution levels (Case Study 4)	time-series data while incorporating spatial and phylogenetic correlations.	projections of future air pollution levels, although these could be hypothesised if existing data are not available.
12. Estimating the threat of **chemical pollution** to biodiversity	Assessing biodiversity changes in response to a reduction in the use of harmful chemical pollutants	• Use a regression framework to allow for time series modelling of both abundance and distribution (e.g. GLM, MARS, GAM, BH). To allow for better handling of uncertainty, Bayesian methods (i.e. BH) may be most appropriate.	**Low**: Bayesian hierarchal dynamic occupancy models have been used successfully in the past to model pollinator responses to pesticides. But, more broadly, substantial prior scoping would be required to determine chemical pollutants that are a wildlife threat and/or appropriate contemporary data will also need to be identified.

† Model types, as described by Thaxter *et al.* (in prep.). These can grouped according to the general analytical approach used:

- **Regression:** GLM: Generalised Linear (Mixed) Models, MARS: Multi-variate Adaptive Regression-splines; GAM: Generalised Additive (Mixed) Model; BH = Bayesian or hierarchical (e.g. staged) approach
- **Machine-learning and Classification:** CRT = Classification and Regression Trees; RF = Random Forests; BT = Bagging Trees; BRT = Boosted Regression Trees or generalised boosted model; ANN = Artificial Neural Network; DA = Discriminant Analysis; SVM = Support Vector Machines; ME = Maximum Entropy; GARP = Genetic Algorithm for Rule-set Production
- **Envelope:** ENFA = Ecological Niche Factor Analysis; BC = BIOCLIM; DO = DOMAIN; MD = Mahalanobis Distance;
- **Other:** EN = ensemble

7 Research scenario case study proposals

7.1 Estimating the effects of proposed garden village developments on bird communities

The government is instigating major increases in house building and infrastructure investment to address the UK housing crisis (Department for Communities and Local Government 2017; Department for Communities and Local Government 2016; Department for Communities and Local Government 2018a). They have put plans in place to create ten new garden towns and cities, and 14 new garden villages across the country (Department for Communities and Local Government 2017), as well as pledging 300,000 extra homes per year by the middle of the next decade. Urban development can come at a significant cost to wildlife, with urbanisation considered to be one of the greatest current threats to global biodiversity (McKinney 2002; Seto *et al.* 2012). To address this, the UK has committed to integrating biodiversity values into planning and development to help with realising Aichi Targets (CBD & UNEP 2011; JNCC & DEFRA 2012). Encouragingly, the new 25-year environment plan (25YEP) has outlined proposals to embed biodiversity net gains approaches into development in the UK and to strengthen standards for green infrastructure (HM Government 2018; DEFRA 2018a). Indeed, it has been widely recognised that biodiversity-friendly urban development has the potential to deliver benefits for both wildlife and people, by incorporating conservation and ecosystem services objectives (Sadler *et al.* 2010; Ikin *et al.* 2015; Plummer *et al.* in revision). However, designing cities, towns, villages or simply new housing estates that truly are more sensitive to biodiversity requires an accurate understanding of how biodiversity is likely to respond to novel urban development scenarios.

To successfully integrate conservation or ecosystem service objectives into future urban development, it is fundamental that we better understand how species' distributions are influenced by patterns of urban landscape composition and configuration. Recent research by BTO using Breeding Bird Survey (BBS) data, and funded by JNCC, has been instrumental in quantifying relationships between bird densities (57 species) and high resolution, spatially explicit details of urban landscape form (derived from OS MasterMap, OSMM) throughout the UK (Plummer *et al.* in revision). Predictive models based on these generalised relationships could provide an important tool in helping policy-makers, planners, developers and homeowners to improve the ecological value of existing and future urban landscapes. More specifically, predictive modelling could be used to estimate the bird (biodiversity) consequences of different arrangements of urban form components in different locations, therefore helping to maximise the local benefits of development for wildlife as well as minimising the national-scale negative impacts. However, to make this possible, further research is now required to refine and test predictive models, so that we can more closely scrutinise, and optimise, the accuracy with which biodiversity predictions are extrapolated under novel urban form scenarios.

Building on the 2018-19 TSDA research by Thaxter *et al*. (in prep.) (which comprehensively evaluated different statistical methods for generating predictions and for assessing predictive performance), existing bird-habitat models based on BBS and OSMM data can be converted into effective predictive models. In particular, cross-validation methods can be used to assess predictive 'out-of-sample' accuracy (Wenger & Olden 2012). By comparing model validation statistics, such as mean absolute error (MAE) (Willmott & Matsuura 2005), it will be possible to select among competing models, based on validated predictive performance, and therefore optimise the accuracy of modelled predictions (Wenger & Olden 2012). This would allow the suitability of different model types to be compared, notably generalised linear mixed models (GLMM) versus Bayesian hierarchical approaches, both of which have been identified as being effective for extrapolating abundance data through space (Thaxter *et al.* in prep.). This approach would also be beneficial in identifying the most important model predictor and covariate terms, in a similar way to an Information Theoretic model selection process. Species' models showing good predictive performance can then be used to predict bird abundances in response to publicly available planning proposals for the UK's new garden villages, e.g. Long Marston (https://www.stratford.gov.uk/planning-regeneration/long-marston-airfield-spd.cfm). Further, manipulation of garden village proposals (e.g. increasing tree cover or removing a waterbody using GIS) can be used to generate additional landscape design scenarios, enabling key habitat features and potential environmental enhancements to be identified. Similarly, this could also be used to identify potential 'tweaks' to garden village proposals that would help in addressing specific biodiversity conservation or ecosystem services objectives.

The outputs from this research would increase the profile of BBS and add a new area of application. The approaches developed could be extended to other taxa/ schemes, especially structured schemes giving abundance data. Work on opportunistic biological records would begin with basic models of dependence upon landscape and habitat but could exploit the same data sources and variables as have been used for BBS analyses, i.e. using existing code and data for urban form. Ultimately, this body of work has the potential to be highly influential in advancing wildlife-friendly urban development in the UK.

7.2 Assessing pollinator responses to the restoration of wildflower-rich grassland, meadows and heathlands, in close proximity to urban and sub-urban environments

As part of the 25 year environment plan (25YEP), the government intend to implement a Nature Recovery Network (NRN) (HM Government 2018). The NRN is a land management strategy, focussed on delivering the core recommendations of the Lawton report (Lawton *et al.* 2010). This strategy has a combined goal of restoring and protecting wildlife, while also increasing the societal benefits associated with increased public access to green space. An action with direct links to the delivery of the NRN within the 25YEP is to consider how landscape-scale restoration of wildflower-rich grassland, meadows and heathlands could improve habitat for pollinating insects alongside providing better public access to high quality green space. Assessing the potential implications of this action is of utmost importance given the vital role pollinators play in food security, and the equally important well-established link between public access to green space and human well-being.

Bee and hoverfly species are considered key pollinating insects in the UK and are therefore the key target species of management actions aimed at promoting insect pollinators. Large-scale, long-term occurrence records are available for these taxa from the Bees, Wasps and Ants Recording Society (http://www.bwars.com/) and the UK Hoverfly Recording Scheme (http://www.hoverfly.org.uk/). These opportunistic biological records are a valuable source of data that can be utilised in a predictive modelling framework, but given the data were collected without a standardized protocol, several forms of bias (e.g. variation in recorder effort through time) need to be accounted for. Simulation studies have shown hierarchical modelling frameworks are particularly well-suited for modelling opportunistic biological records (Isaac *et al.* 2014), where variation in detectability is simultaneously accounted for, whilst estimating the ecological processes of interest.

In order to predict pollinator responses to restoration of wildflower-rich grassland, an essential step is to estimate pollinator associations with, and response to changes in, the given habitat. Species distribution models (SDMs) are frequently used to model the relationship between species occurrence and various environmental variables (Thaxter *et al.* in prep.). This relationship can then be used to predict species responses to potential future environmental scenarios. While useful, SDMs tend to ignore the temporal component of data, potentially limiting the sensitivity of the models to environmental predictors that display strong temporal variation. Dynamic occupancy models differ from traditional occupancy models and SDMs in that they explicitly model drivers of site colonisation and extinction, making greater use of spatiotemporal data, and ultimately have improved prediction accuracy (Guillera-Arroita 2017). They grant a greater understanding of the processes driving species expansion or decline, allowing the user to predict potential status of species under future environmental scenarios. Woodcock et al. utilised a dynamic occupancy modelling framework to estimate the impact of several pesticides on bee species in Britain (Woodcock *et al.* 2016). Furthermore, they predicted the current status of bee species under a scenario where pesticides had no impact on the species.

Hierarchical dynamic occupancy models could be used to analyse opportunistic biological records, to estimate bee and hoverfly associations with wildflower-rich grassland, meadows and heathland. These models could then be used to predict changes in pollinator biodiversity (richness, and other diversity metrics) in response to policy interventions specifically aimed at increasing the coverage of wildflower-rich grassland, meadows and heathland in close proximity to urban and sub-urban environments. Spatially explicit future scenarios could be built using available tools (such as the InVEST pollination model and the *lulcc* R package). Here, the likelihood of any given habitat being converted into wildflower-rich meadows and heathland would be estimated based on past habitat transitions. This could then be combined with social science data on the distance people tend to travel to experience green space, to inform a rule governing the maximum distance from urban/suburban landscapes to conduct habitat restoration. Percentage cover of the key habitat variables can be extracted from the CEH land cover maps and would form the basis of the environmental predictor variables used in these models.

Key outputs from this modelling framework would include species-specific associations with the key habitats of interest (wildflower-rich grasslands, meadows and heathland). Additionally, predictions of pollinator response to targeted habitat restoration, in the form of species-specific changes in status (for example, percentage change in distribution range) and composite metrics of change in pollinator diversity, for example mean change in range size across all species and change in pollinator richness. Finally, a particularly interesting and important output will be estimates of past, and future predictions of, *effective biodiversity change*. Here, *effective biodiversity change* reflects the patterns and changes to pollinator biodiversity that your average person will actually experience. Again, given the links between biodiversity and human well-being, it is vital that we improve our understanding (and predictions) of the localised trends in biodiversity that people experience.

7.3 Assessing biodiversity responses to increasing the coverage, and status, of SSSIs

Protected areas are widely considered to be a valuable strategy for combating biodiversity loss. This value is reflected in the Convention on Biological Diversity's Aichi Target 11 that calls for a global increase in protected area coverage. Furthermore, both the Biodiversity 2020 strategy and the 25YEP have actions to increasing the number of Sites of Special Scientific Interest (SSSIs) in favourable condition. Specifically, the 25YEP aims to restore 75% of our one million hectares of terrestrial and freshwater protected sites to favourable condition. SSSIs make up the majority of protected areas in the UK (Gaston *et al.* 2006). The core goal of the SSSI network is to protect natural and semi-natural habitats from development, whilst implementing management plans that benefit biodiversity. Alongside the Biodiversity 2020 and 25YEP goals of improving the condition of the SSSIs, the 25YEP has an action of creating or restoring 500,000 hectares of wildlife-rich habitat outside the protected site network, focusing on priority habitats as part of a wider set of land management changes providing extensive benefits and effectively increasing the coverage of the protected area network in the UK.

Using a similar methodology to Case Study 2 (above), it is possible to model past responses of species to coverage and status of protected areas. These responses can then be used to predict biodiversity responses to scenarios of increased coverage and status of SSSIs. Such models require spatiotemporal data on protected area coverage and condition. These data are available from the World Database on Protected Areas (IUCN & UNEP-WCMC 2015), which can be used to derive a measure of percentage cover of protected land within each grid cells (1 x 1km or 10 x 10km), including the date of designation. Spatiotemporal data on SSSI condition are available from the Statutory Nature Conservation Bodies (SNCBs). Again, as with Case Study 2, future scenarios could focus solely on temporal change, here, focussing on change in total coverage and status of SSSIs. For example, a particularly promising scenario with direct relevance to the 25YEP would involve predicting biodiversity responses to increased proportion of SSSIs in favourable condition, moving from the current proportion of approximately 50% of SSSIs in favourable condition (see C1 of the UK biodiversity indicator set (Department for Environment Food and Rural Affairs 2018b)) to 75%. Biodiversity 2020 looks to consider biodiversity offsetting as a systematic approach to nature planning, while the 25YEP has a goal to embed an environmental net gain policy to development (including housing and infrastructure) and plans to explore ways in which national spatial data and strategies could support and improve the benefits achieved through environmental net gain. By employing spatial conservation prioritisation methods (see Haight & Snyder 2009) with these goals in mind, it would be possible to produce spatially explicit projections of potential protected area coverage, which in turn could be used to predict species responses to said projections.

Priority species are an ideal candidate group for study here, given protected areas are often designated for the protection of species of conservation concern. Such models could be extended onto other groups of species, for example key functional groups such as pollinators. This approach can be applied to both species' abundance and distribution data, with the core principle being the need to estimate species-specific responses to protected area coverage and condition. Opportunistic records could be analysed following the methods of Case Study 2, noting the need to account for the various forms of bias. While abundance data, such as the BBS abundance data, could be analysed using similar methods to those developed for Case Study 1.

Key outputs from this Case Study would be estimates of species-specific responses to protected areas coverage and status. These could be combined to assess current and past effectiveness of the protected area network, addressing questions such as "has the protected area network directly benefitted species of conservation concern?". Finally, these models would generate predictions of biodiversity responses to future protected area scenarios. These would include changes in species richness and other diversity metrics, and also composite estimates of change in status of threatened (priority), iconic or economically important species.

7.4 Estimating changes in species abundance in response to projected changes in air pollution levels

Human deaths attributed to air pollution are rising at an alarming rate. In 2016, 91% of the world's population was living in places where air pollution levels exceed the World Health Organisation (WHO) air quality guidelines and air pollution was considered to be responsible for 4.2 million premature deaths (World Health Organisation 2018). Consequently, air pollution has been identified as the biggest environmental health risk to date and is currently a global health priority (World Health Organisation 2018; World Health Organization 2016).

There is also evidence that air pollution may have severe impacts on other organisms (Reich & Amundson 1985; Lovett *et al.* 2009; Llacuna *et al.* 1993) which can result in changes to the composition and diversity of ecosystems (Lovett *et al.* 2009). Birds are thought to be particularly vulnerable because their respiratory system uses uni-directional airflow and cross-current gas exchange which enables more efficient transfer of molecules between the atmosphere and their blood (Brown *et al.* 1997). A recent review found that air pollution can cause respiratory distress, suppress immune systems, impair reproductive success and even reduce species diversity and richness (Sanderfoot & Holloway 2017). But currently data are limited, with very few studies on wild systems and most focused on specific point sources of pollution (Llacuna *et al.* 1993; Sanderfoot & Holloway 2017). There is little understanding of variation in pollution sensitivity between species and at different life stages, though this may be substantial (Eeva & Lehikoinen 1995). Birds are considered to be valuable environmental indicators due to their wide distribution, visibility, sensitivity to environmental change, and relatively high trophic status. Therefore, improved knowledge of the effects of air pollution on birds could potentially assist in assessments of air quality for human health and may also aid in the conservation of other, more elusive taxa. Furthermore, we have a duty to conserve bird populations under national and international law, so it is important to understand the extent of threat which we need to account for in future conservation efforts (Lovett *et al.* 2009; Sanderfoot & Holloway 2017).

Through the development of models of the large-scale associations between air pollutants and patterns in bird abundance and trend, based on national-scale multi-species analyses, it would be possible to make predictions about likely population impacts of different levels of air pollutants. Specifically, bird abundance data (BBS dataset) can be combined with two sources of air pollution data, Modelled Air Quality and the Automatic Urban & Rural Monitoring Network (see Table 3) in order to quantify both spatial variation and the temporal relationship between air pollution and bird population trends. Variation in the form of those associations in relation to species' ecological characteristics (e.g. preferred habitat, foraging guild) will help to identify potential underpinning mechanisms. Further, by focusing on common background emissions, specifically, Particulate Matter (PM) and Nitrogen Dioxide (NO_2), rather than point sources of pollution, this we ensure the modelling outcomes have broad policy relevance. PM is often used to represent air pollution levels more generally and has been found to be particularly detrimental to human health through its absorption of toxic heavy metal (HM) particles (World Health Organisation 2018; World Health Organization 2016; Bollati *et al.* 2010) and NO_2 has previously been linked to declines in bird populations in cities (Peach *et al.* 2018; Peach *et al.* 2008).

Generalised Additive Mixed Models (GAMM) can be used to model these non-linear relationships flexibly in space and time. These can be used to model the effect of key air pollutants (e.g. PM_{10}, $PM_{2.5}$ and NO_2) on abundance and population trends of multiple species, while also incorporating spatial and phylogenetic correlations. Further consideration of the species selected for modelling will be necessary to maximise the potential to generate models for prediction. In particular, species should be chosen to ensure: 1) sufficient data to generate a long-term trend, 2) coverage of a wide variety of functional groups (e.g. predators, granivores, insectivores) and 3) year-round residency to avoid confounding effects of contact with pollutants on migration or in wintering areas. Models will also need to include relevant environmental data (i.e. habitat, elevation, tree cover) to account for the effects of other environmental gradients.

These models can then be used to predict both the effects of a range of emission reductions (from 0-80) and the effect of the future predicted increases in emissions (Department for Business 2018) on the abundance and population trend of birds. This approach will enable the comparison of species in their response to different air pollutants, and predictions of the future composition of our birdlife under different emission scenarios. In particular, it can be used to estimate the bird (biodiversity) impacts of the UK government's planned emission reduction target of 57%. Further, predictive models have the potential to provide a strong evidence base for selection of future emission targets, suitable for the preservation the UK's bird populations, by quantifying the risk posed by future emissions if no action is taken and enabling selection of the level of emission decrease that would give the best balance between preserving bird populations and minimising economic costs.

8 Conclusions

The predictive modelling tools capable of tackling the research priorities raised here are largely well-established, as reviewed by Thaxter *et al.* (in prep.). However, the appropriate data and ecological knowledge to support them are frequently lacking, as detailed in **Table 4**. As such, the feasibility of addressing many of these priorities is limited without undertaking substantial preliminary research to address knowledge gaps, scope potential data sources and develop informed research proposals.

Fundamentally, making new predictions will be considerably easier if relevant models explicitly describing biodiversity responses to particular drivers already exist (e.g. Case Study 1). Having 'pre-prepared' models readily available means that, in theory, to make future predictions, all that is required is to assess their predictive power and to apply them to novel scenarios. Space-for-time approaches have a role here for datasets that lack a temporal component. Furthermore, if similar (rather than exact) models exist, these too could facilitate predictive model development. For example, models of the effect of climate on a species in one region could inform models in another region. Even if different data are involved, this would still provide a clearer starting point for developing alternative predictive models than simply having a hypothesis about possible effects. In other words, projects requiring models to be developed from scratch would be much more time-consuming. Therefore, we anticipate that there will be a trade-off between developing a "best" predictive model from scratch and applying an existing analysis in a predictive context (with caveats).

To ensure the viability and reliability of predicted biodiversity responses, it will also be essential that suitable variables for the drivers of interest are identified or produced to inform predictive model building. For example, though we present a number of potential predictor data sources in **Table 3**, in many cases we are yet to determine whether these represent the necessary spatial/temporal extents or resolutions necessary to test biodiversity responses. In particular, newly created habitats (e.g. in the context of Research Priorities 2, 3, 4 or 6) may take decades to mature. Therefore, predictions from a contemporary context may not be informative, since taxon responses are likely to depend on stochastic factors (such as chance colonization effects) as well as habitat relationships, and it is likely that the background habitat, population and climate contexts will be very different by the future time at which the specific habitat conditions being modelled are relevant. Further, predictive models are likely to be developed using land cover/ land-use variables which might only describe ultimate or goal habitats or might be poor descriptors of habitat condition, particularly in relation to ecosystem service delivery. However, biodiversity responses are likely to depend upon intermediate states, especially within a given timeframe. Dynamic models, accounting for species associations with habitat structure or age, are ideal in the context of predicting the impacts of future land cover scenarios. But to generate accurate prediction, they require (a) knowledge of relationships with intermediate (e.g. early successional) states and (b) spatial data on those intermediate habitats. This may limit the species and/or habitats for which predictive models can be developed.

Data for pressures such as air, chemical or light pollution are also likely to be especially problematic due to their close association with other, potentially confounding land cover/ land-use drivers. Nonetheless, it is evident that there are a wealth of fine-scale, spatially and temporally explicit data available to support predictive modelling (**Table 3**), with many of these already being used extensively to understand the impacts of environmental and anthropogenic pressures on UK wildlife.

Where existing knowledge, data and models do exist, we show here that there is significant potential to successfully use predictive modelling to inform species conservation, landscape management and policy. In particular, we have presented examples of how these might play out in the context of future urban development and landscape-scale restoration in the UK, in line with Government priorities identified by the 25YEP and substantiated by the recommendations from the TEPoP discussions.

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