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PERSPECTIVE

Biodiversity, Planning and Development – Towards Best Practice

Monitoring protected areas by integrating machine learning, remote sensing and citizen science

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Abstract

1. Protected Areas (PAs) are central to addressing the world's biodiversity crisis, but their effectiveness for conservation varies. Therefore, high-resolution habitat condition monitoring is needed to evaluate their individual impacts. Critically, monitoring must efficiently scale to cover large areas and be conducted at regular intervals.
2. Remote sensing (RS) data and citizen-science (CS) species data are two sources of global data available for habitat condition monitoring, and integrating these could provide high-resolution, scalable biodiversity data required for the detailed monitoring of PAs. However, integrating these presents four data analysis challenges: RS data are large and complex, large-scale CS data are biased, integrating RS and CS data is non-trivial, and fine-tuning to local priorities is required.
3. Machine Learning (ML) methods can address these challenges: geospatial foundation models for RS data can compress large data volumes, ML de-biasing techniques can improve CS data quality, deep learning and multimodal ML can help to integrate RS and CS data, and transfer learning can fine-tune models to local priorities. Here, we review these techniques and discuss how they can be applied to habitat condition monitoring.
4. *Practical implication*. Together, these advances in ML can deliver high-resolution biodiversity data that can be tailored to local priorities, enabling the efficient monitoring of PAs at scale, with the potential to support spatial land use decision-making.

KEYWORDS
biodiversity, citizen science, habitat condition, machine learning, protected areas, remote sensing

1 | INTRODUCTION

Countries worldwide have made commitments to reverse the ongoing decline in species diversity and abundance (CBD, 2022; Díaz et al., 2019). One important pathway for restoring biodiversity is through Protected Areas (PAs) (Langhammer et al., 2024), and the Convention on Biological Diversity (CBD) has set a target of protecting 30% of land and sea by 2030 (30 × 30) (CBD, 2022). Yet, the effectiveness of PAs depends on their "adequate implementation, enforcement, monitoring, and long-term protection" (Bailey et al., 2022). Taking the UK as one example, over 50% of PAs are assessed as 'unfavourable condition' (Starnes et al., 2021), and PA biodiversity is generally in decline (Brighton et al., 2024; Cooke et al., 2023). To address this, PA condition and the effectiveness of PA management must be assessed with monitoring at sufficiently high spatial, temporal and taxonomic resolution, yet, the majority of UK PAs are not regularly monitored (Bailey et al., 2022; Dudley et al., 2016; Robinson et al., 2024; Starnes et al., 2021). Additionally, such high-resolution data, particularly on biodiversity, are needed by local planning authorities to integrate conservation into spatial planning decisions, and to monitor 'other effective area-based conservation measures' (OECMs) (Baker et al., 2021; Dalton et al., 2023; Kremen & Merenlender, 2018; Perino et al., 2022).

Data from biodiversity surveys are important in describing PA condition, but field-based biodiversity monitoring data is limited. As demands for near real-time, high-resolution information grow, it becomes infeasible to scale field-based monitoring to the ideal scenario where condition monitoring has high spatial resolution (for informative spatial planning), spans large areas (to incorporate the effects of surrounding landscapes), encompasses a wide set of biodiversity indicators (to plan for and evaluate secondary effects), is repeated regularly over time (to monitor progress) and aligns with local biodiversity priorities (to be applicable locally; Galbraith & Stroud, 2023). Biodiversity policymakers have highlighted the demand for scalable methods to measure habitat condition (or quality), and the need to integrate different remote and in situ data sources (Moersberger et al., 2024).

In this perspective, we argue that Machine Learning (ML) methods can enable the monitoring of PA habitat condition from remote sensing (RS) data, calibrated using citizen-science (CS) species records (Figure 1). Both RS and CS data sources are readily available and can be combined to map habitat condition (specifically, species data as an indicator of condition) at high resolution and tailored to local priorities (Anderson, 2018; Dalton et al., 2023; Galbraith & Stroud, 2023; Nagendra et al., 2013; Perino et al., 2022). RS data provide comprehensive, high-resolution and regularly sampled data on land cover and land use (Skidmore et al., 2021; Timmermans & Kissling, 2023), but lack direct measurements of species (diversity) that can indicate habitat quality. CS data provide direct assessment of habitat condition (as indicated via species data) via irregularly sampled species records (Chandler et al., 2017; Mandeville et al., 2023). While RS and CS data are often used for bespoke species distribution modelling, we argue they can also facilitate high-resolution habitat condition monitoring of PAs if four data analysis challenges are overcome.

In the following, we will review these challenges and the potential of ML methods to address these. Previous studies have demonstrated that ML models can extrapolate ecologist expert knowledge to scale up analyses (Antonelli et al., 2023; Greenhill et al., 2024; Van der Plas et al., 2023; Virkkala et al., 2022), which will be crucial for monitoring habitat condition in high resolution at a landscape scale. While previous work has reviewed such applications as well as future trends of ML for ecology and conservation science (Pettorelli et al., 2024; Pichler & Hartig, 2023; Tuia et al., 2022, 2023), here we focus specifically on how ML could facilitate high-resolution monitoring of PAs.

2 | AVAILABLE DATA AND METHODS

Large-scale, high-resolution data are required for efficient condition monitoring in PAs. Two relevant data sources with global coverage are RS and CS data, which would benefit from a joint analysis: CS species records are valuable to specify the relevant 'features' in RS data, while RS data can interpolate between sparsely distributed CS

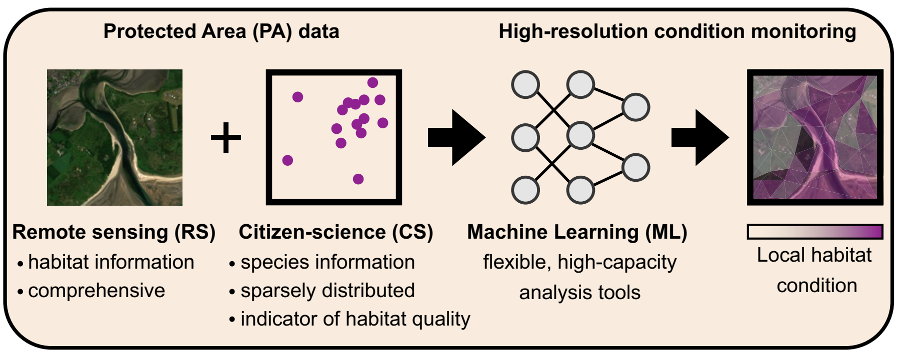

FIGURE 1 Sketch outlining that remote sensing (RS) and citizen science (CS) provide large-scale biodiversity data for Protected Areas (PAs), which can be integrated using Machine Learning (ML) to generate high-resolution, scalable biodiversity indicators such as habitat condition. Satellite image from ESA Sentinel-2.

records (Anderson, 2018; Antonelli et al., 2023). Together, they form the basis of a comprehensive and updatable data product at high spatial resolution, which can inform spatial biodiversity planning in PAs and beyond (Figure 1).

2.1 | Remote sensing (RS)

RS data is an umbrella term for all data of the Earth's surface obtained with remote sensors, for example mounted on satellites, aeroplanes and drones, and often also referring to other (remote sensor-derived) geospatial products such as maps and meteorological data (Campbell et al., 2023). RS data, especially those from satellites, are well suited for large-scale condition monitoring, with extensive coverage and repeated measurements obtained evenly across their area of interest (Pettorelli et al., 2024; Skidmore et al., 2021; Timmermans & Kissling, 2023).

Given the high volumes of these data sets and the complexity of detailed downstream analysis, RS data is often used by end-users in a processed form, such as vegetation indices or land cover maps (García-Álvarez et al., 2022). Derived RS products are sometimes used as a proxy for ecological habitats (Koma et al., 2022; Weber et al., 2018), but this application is not always possible, for instance, when species-specific information is not captured by the land cover schema because of changing conditions (e.g. vegetation health, water levels), habitat structure (e.g. fragmentation, edge effect) and complex habitats (e.g. mosaics, artificial habitats such as plantations and urban green space) (Lumbierres et al., 2022; Tomaselli et al., 2013). Instead, directly analysing RS data, rather than relying on derived classifications, can better account for such complex habitat information (Pettorelli et al., 2024; Skidmore et al., 2021) for predicting species presence (Teng et al., 2023) and protection designation (Greenhill et al., 2024).

2.2 | Citizen science (CS)

Here, we refer to CS biodiversity data as species records obtained by volunteers, readily available on CS data platforms, varying from unstructured (opportunistic) records (e.g. by photo identifications from mobile applications) to standardised surveys (Johnston et al., 2022; Pocock et al., 2017, 2018). The rapid increase in CS data and its increasing spatial coverage, from local to international scales, makes it an essential source of information for biodiversity monitoring (Callaghan et al., 2021; Mandeville et al., 2023): the iNaturalist project alone has nearly a quarter of a billion species records (as of December 2024). CS data is often available in standardised formats on biodiversity data platforms such as GBIF (Global Biodiversity Information Facility, www.gbif.org), which facilitates the large-scale data analysis of species records. CS data now accounts for the vast majority of all biodiversity data available on GBIF, and is the only biodiversity data source available (on GBIF) for 25% of PAs globally (Mandeville et al., 2023).

2.3 | Machine learning (ML)

ML models differ from conventional statistical analyses by their ability to learn to infer the most relevant data features to solve a task, rather than being confined to a set of pre-defined features. This creates flexibility, and makes ML especially useful for analysing large data sets, where the predictive data features are either unknown or difficult to extract (but also creates some challenges, e.g. around interpretability and handling data bias; Pichler & Hartig, 2023). One of the hallmark techniques of ML is deep learning, where multi-layered models learn to extract abstract data representations to solve complex tasks (see Borowiec et al., 2022 for a review). For example, to detect individual trees in a RS image, a model has to learn to recognise tree crowns despite their variety in appearance; once it has done this, it can be applied at scale (Weinstein et al., 2020). To achieve this, models require 'annotated' example data (i.e. data accompanied by labels that describe the objects of interest), and as a rule of thumb, more annotated data is required as the complexity of either the data or task grows. For example, as we seek models to assess PA condition, ML models could be trained on RS data annotated with CS species data.

3 | OPEN CHALLENGES FOR INTEGRATING RS AND CS USING ML

We identify four data analysis challenges in combining RS and CS data that ML can help address (Figure 2). In the following, we review each of these, including the ML techniques that provide ways forward.

3.1 | Compressing large RS data

RS data is collected at an enormous, petabyte scale, far outweighing the data volumes used to train modern-day large language models (Rolf et al., 2024): it has wide spatial coverage at high resolution, stacking of different data (of different sensors, spectral bands and auxiliary geospatial data layers) and repeated measurements over time. The richness of RS data presents both an opportunity and a challenge, especially for rarer species which can, by definition, be good indicators of habitat quality. In principle, increasingly complex RS data can distinguish between a greater variety of habitats and habitat conditions, which benefits the monitoring of habitat-specific rarer species (Crisfield et al., 2024). Simultaneously, CS observations of rarer species may be scarce, which presents a challenge for training ML models where, traditionally, large annotated data sets are required. This distinguishes RS data analysis from other computer vision applications, such as categorising photographs, where the dimensionality of input images is typically lower (e.g. non-repeated, 3-band images) and labels are easier to acquire (images can be annotated directly, whereas remote sensing annotations often require ground surveys; Rolf et al., 2024).

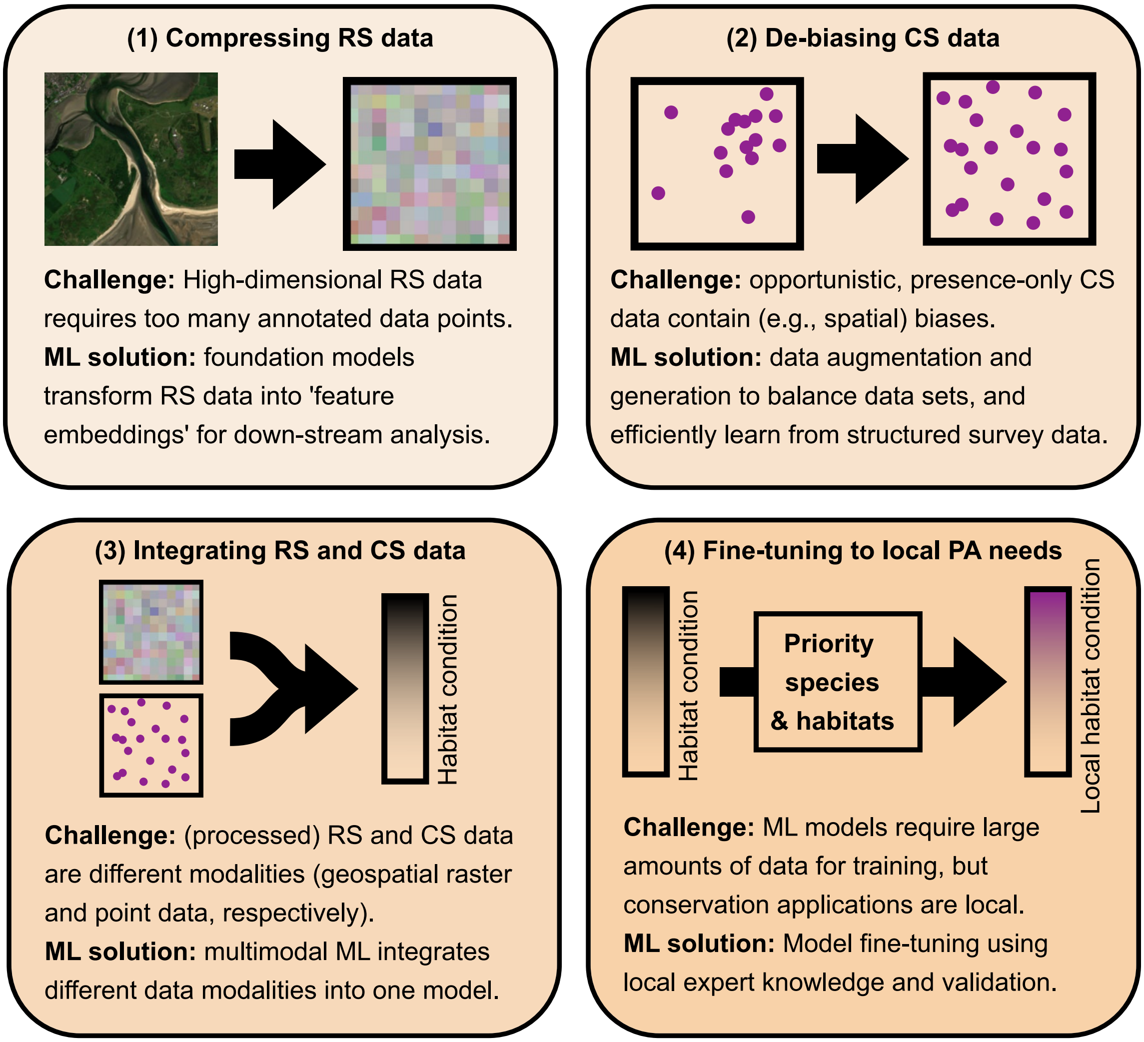

FIGURE 2 Four challenges need to be overcome to deliver high-resolution biodiversity information, which can be addressed by advances in Machine Learning (ML).

To address this challenge, ML research has focused on the development of pre-trained 'geospatial foundation models' that transform high-volume, raw RS data into abstract representations (called 'embeddings') that capture multi-resolution features of the input data more efficiently (Cong et al., 2022; Klemmer et al., 2023; Rolf et al., 2021; Rußwurm et al., 2024; Tseng et al., 2023), and can integrate RS data with different spatial resolutions via scale-aware positional encoding (Reed et al., 2023). Embeddings can greatly reduce the amount of annotated training data required, because their more efficient representation makes it easier for models to identify the relevant data features (Tuia et al., 2023). To learn effective embeddings, geospatial foundation models use a learning paradigm called self-supervised learning, whereby models are trained using inherent properties of the data, alleviating the need for annotation, which would be resource-intensive. For example, with self-supervised learning, a ML model can be tasked to identify the same location across different seasons (Manas et al., 2021) or to reconstruct artificially partly-obscured satellite images (Cong et al., 2022; Tseng et al., 2023). Although these tasks are not directly relevant to the desired application (such as predicting biodiversity), the data features that the model learns to recognise—captured in the embeddings—are. A task-specific model is then trained on these embeddings using annotated data samples, greatly reducing the volume of annotated data needed to solve the task at hand (Pettorelli et al., 2024).

In conclusion, geospatial foundation models 'compress' RS data which particularly improves prediction accuracy when few annotated data are available (so-called 'few-shot learning') (Rußwurm et al., 2024). This not only reduces the resources needed for data annotation, but also creates new possibilities for when the annotations via CS data are scarce but modelled information is particularly valuable, such as in low-data, high-biodiversity regions in the global South, or distribution modelling for rare species.

3.2 | De-biasing CS data

CS data provide a crucial data source for monitoring biodiversity at scale (Burns et al., 2023; Middlebrook et al., 2023), providing both a high number of data points and broad spatial coverage. Presence-absence data (strictly, presence/non-detection data) is particularly informative for analyses and can be obtained from more structured CS reporting, logging the presence (or number) of all species (within a taxonomic group of interest). However, there is vastly more 'opportunistic' CS data, available as single species observations (i.e. presence-only data) reported from as and when the observer chooses. The analysis of presence-only CS data will be crucial for large-scale, high-resolution biodiversity monitoring of PAs and OECMs, and so addressing the biases of these data remains a core challenge (Johnston et al., 2022).

All CS data is uneven in coverage in space, time and taxon, but presence-only CS data can be especially biased, by location (locally, e.g. proximity to paths or nature reserves, and nationally, e.g. variation between countries), time (e.g. changes in the observer pool and expertise over time) and species (depending on, e.g. detectability, rarity and appearance) (Johnston et al., 2022). These data biases pose a challenge for training ML models, because, if unaccounted for, they can be reflected in model predictions; e.g. an ML model may learn that species 'presence' is related to presence of paths, even though this is a detection bias (Mehrabi et al., 2021). When training ML models, it is important to account for these biases.

The first approach is to de-bias the CS data, by either subsampling overrepresented data or generating and augmenting underrepresented data. Subsampling is not ideal because available data is discarded; this is especially problematic for rare species (Steen et al., 2021). In ML, 'data augmentation' (generating variations of existing data points) and 'synthetic data generation' (generating new data points) are common techniques to deal with biased or low-volume data sets (Mumuni & Mumuni, 2022). The latter technique is already commonly applied in ecology, through the generation of pseudo-absences to supplement presence-only data (Beery et al., 2021), and ML can do this efficiently (Cole et al., 2021). Alternatively, data can effectively be de-biased by adjusting a ML model objective ('loss function') to counteract biases in the data (for example, by weighting species with few observations more heavily; Zbinden et al., 2024). Although these techniques can improve predictions based on biased data, the resulting uncertainty can be high, so it is critical to incorporate uncertainty quantification methods to provide meaningful predictions (see Gawlikowski et al., 2023 for a comprehensive review; Lehmann et al., 2024 for a ML uncertainty quantification toolbox). Examples based on CS data include 'double machine learning' to estimate the uncertainty of spatial abundance trends of bird species (Fink et al., 2023), and conformal prediction for insect species image classification, where the model predicts a larger set of possible species when uncertainty is high (Chiranjeevi et al., 2025).

The second approach is to develop models that integrate structured and opportunistic CS data (Isaac et al., 2020; Johnston et al., 2022). Ideally, this draws on the best of both worlds: models learn to make unbiased predictions from the structured data, but can increase their spatial resolution by leveraging opportunistic data points. Developments in this area are encouraged by GeoLifeCLEF, an annual competition to train ML models on a benchmark data set that mixes presence-absence with presence-only data (Botella et al., 2023). The 2023 winning team, Ung et al. (2023), demonstrated that the best strategy is to use both presence-absence and presence-only data, introduced at different stages during training.

3.3 | Integrating RS and CS data to assess PA condition

There are two main ways to integrate RS and CS data, which can be enhanced by ML. First, by predicting CS species records from RS data, commonly referred to as species distribution models (SDMs), and then using the multi-species output from the SDMs as indicators of habitat condition, as informed by local expert knowledge. Second, RS and CS data can simultaneously serve as input data to directly indicate some metric of biodiversity value or PA/habitat condition, although this requires sufficient independent data on condition.

SDMs are a well-established ecological tool that offer several advantages for predicting habitat condition: first, species data can be used as data annotations for ML, and these are more readily available via CS than more comprehensive metrics of biodiversity (e.g. species richness) or independent measures of habitat condition. Second, predictions of species presence are straightforward to interpret, and relatively easy to verify in the field. For example, to measure the condition of woodlands, SDMs could first predict the presence of indicator species from RS data, and these (verifiable) predictions are then used as indicators for woodland habitat condition (Vallecillo et al., 2016). This verifiability also improves model interpretability, which is an important trait for ML models to be trusted and applied in practice (Beery et al., 2021). Deep learning in ML has improved SDMs by their ability to predict the joint occurrence of multiple species, making use of shared predictive features in the data, which improves overall accuracy (Cole et al., 2023; Teng et al., 2023). Further, ML computer vision methods analyse RS images in 'full', which enables SDMs to use richer feature data, including from the wider surroundings which helps to account for potential spatial inaccuracies of species records (Teng et al., 2023). Other ML techniques can further improve predictive performance based on presence-only data, such as gradually bootstrapping species imbalance or resampling records from nearby locations (Kellenberger et al., 2022), or directly compensating for the incompleteness of presence-only data (Cole et al., 2023). The downside of SDMs is that they confine the researcher to using species biodiversity as indicators, even when expert assessments of habitat condition are available.

Alternatively, RS and CS data can both be used as input data to predict a direct measure of habitat condition or biodiversity (Andermann et al., 2022). This requires (resource-intensive) habitat condition assessments to train and validate models, but can draw on the combined information of RS and CS records to make predictions. Integrating RS and CS data is not straightforward, as RS data is usually ubiquitously available as raster data (where each pixel corresponds to an area of the same size), while CS data is usually stored as irregularly distributed point data. Multimodal ML techniques for integrating raster and point data are required, such as estimating densities or rasterised distributions from point data (Andersson et al., 2023; Fink et al., 2023).

3.4 | Fine-tuning to local priorities using expert validation

In the 'pre-train/fine-tune' framework, ML models are first pre-trained on large data sets (at the national/global scale), and subsequently, only a fraction of model parameters are updated during a fine-tuning stage were the model is trained on local data (Chu et al., 2016; Han et al., 2024). Generally, this strategy works well when some data features (e.g. tree crowns) reoccur across different domains (e.g. different ecosystems) with varying appearance or importance. This enables end-users to fine-tune pre-trained ML models to their local PA priority habitats and species, while benefiting from ML capabilities derived from the large amount of data available more widely (Anderson, 2018; Dalton et al., 2023; Pettorelli et al., 2024). This strategy is more efficient than training models from scratch for each application separately in remote sensing (Rußwurm et al., 2024). Crucially, this allows advanced ML models to be deployed in PAs where little or no CS data is available, by first pre-training them on areas where CS data is abundant and then fine-tuning them with a much smaller number of data points (Teng et al., 2023).

Expert knowledge and validation are crucial to fine-tune models to local needs (Anderson, 2018; Pettorelli et al., 2024). Expert knowledge is needed to identify the target biodiversity indicators, annotate a small amount of new data for fine-tuning, conduct field surveys to validate model predictions in new areas, and to interpret model predictions in conjunction with other local constraints and goals (Dalton et al., 2023). Some fine-tuning could be applied by experts within accessible user interfaces (e.g. GIS-based) without the need for ML knowledge; this has successfully been applied in other scientific disciplines (Mathis et al., 2018).

4 | CONCLUSION

The evaluation and monitoring of policies aimed at reversing nature's decline requires detailed and locally relevant biodiversity data delivered rapidly and at scale. Already, where available, these data have transformed applications for identifying areas suitable for protection or rewilding (Greenhill et al., 2024; Zoderer et al., 2024), the large-scale evaluation of agri-environmental subsidies and ecological restoration (Lake et al., 2022; Ma et al., 2022), and the detection of invasive species (Kaasiku et al., 2021).

In sum, environmental data is available at unprecedented scales in near real-time from satellites via RS, while the abundance of CS recording from hundreds of thousands of volunteers globally could be a source of knowledge to interpret the RS data, i.e. to be used as annotations for training ML models on RS data. We argue that the ambitious data requirements for nature conservation and restoration can be supported by leveraging the potential of ML models to transform monitoring of PAs and our wider environment, by providing CS-derived biodiversity insights at the resolution of RS data. Geospatial foundation models for RS, via ML, open up new opportunities to analyse, in a data-efficient way, the richness of large-scale RS data despite limited annotated data, while de-biasing and data integration can be used to robustly combine RS and CS data. Finally, expert interpretation, validation and fine-tuning can take these large, data-hungry models and efficiently adapt them to local monitoring priorities where CS data are sparser. We have a wealth of environmental data; ML is a tool to help us gain insights.

AUTHOR CONTRIBUTIONS

Writing—original draft: Thijs L. van der Plas. Conceptualisation and Writing—editing and reviewing: all authors.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest to declare. The views expressed in this study are those of the authors and are not necessarily those of the Peak District National Park Authority.

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DATA AVAILABILITY STATEMENT

This manuscript does not include any data.

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