Received: 6 March 2024 | Accepted: 14 August 2025

DOI: 10.1002/2688-8319.70113

BRITISH ECOLOGICAL SOCIETY Ecological Solutions and Evidence

PERSPECTIVE

Creating the vision of rapid, repeatable, reactive data workflows for policy on biodiversity

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Funding information
HORIZON EUROPE Innovative Europe, Grant/Award Number: 101059592

Handling Editor: Marc W. Cadotte

Abstract

1. Effective biodiversity management and policymaking requires timely access to accurate and reliable scientific data on biodiversity status, trends and threats. However, current biodiversity monitoring processes are often time-consuming, complex and irreproducible. Moreover, the quality and types of biodiversity data are diverse, which challenges their integration and impedes effective monitoring. A major step to overcome such challenges would be the availability of standardized species occurrence data. However, challenges arise in aggregating and integrating these heterogeneous data with environmental and landscape data.
2. By creating standardized biodiversity data cubes and automated workflows for post-processing, we envision that (1) information from complex datasets will be available in a known format to efficiently communicate biodiversity variables to policymakers; (2) the adoption of repeatable Open Data workflows will make biodiversity data more accessible, efficient and cost-effective; and (3) cloud computing will make it easier to analyse large datasets, benefit from a broader range of models, share resources and work together on biodiversity projects.
3. This revolution in biodiversity monitoring will rely on community collaboration. By bridging the gap between policymakers' needs, bioinformation specialists' skills and data collectors' motivations, biodiversity monitoring can become a more inclusive and community-driven effort. As such, we advocate for the development

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of tools and workflows in close consultation with stakeholders to enhance the impact and use of biodiversity information.

4. *Practical implication*. The proposed approach faces challenges in maintaining software, data standards and addressing biodiversity data complexity. However, leveraging existing infrastructures like GBIF and Copernicus, and building on the knowledge from GEO and GEO BON offers a feasible path.

KEYWORDS
analysis-ready datasets, biodiversity management, community collaboration, policymaking, spatial and temporal resolution, species occurrence, taxonomic aggregation, trends

1 | INTRODUCTION

Effective biodiversity management and policy decisions depend on timely, accurate and reliable scientific data, including information on current status, trends and threats. Moreover, the ability to predict future changes in biodiversity through modelling is critical for proactive policymaking (Dietze et al., 2018; McIntire et al., 2022). This information then needs to be communicated in actionable and understandable formats, with measures of uncertainty and outcomes from a range of possible scenarios. Many global policy initiatives aim to improve biodiversity monitoring, such as the Kunming-Montreal Global Biodiversity Framework. The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) has worked with hundreds of experts globally to produce global, regional and thematic assessments on the state of biodiversity. All of these efforts have the same message: we urgently need access to up-to-date data and information to be able to measure biodiversity status and trends (Gadelha et al., 2021; Geijzendorffer et al., 2016; IPBES, 2019). Nonetheless, and despite repeated calls for improved biodiversity monitoring (e.g. (Niemelä, 2000)), the steps of data cleaning, aggregation and analysis are time-consuming, convoluted, laborious and often irreproducible.

Biodiversity data collectors are diverse, including amateur naturalists, conservation groups, non-governmental organizations, pest controllers, land managers, farmers, ecologists, researchers, planners, harvesters of natural resources, museums, herbaria and others. They are the creators, funders and users of biodiversity data, such that they form a network with a stake in this knowledge and a long-term interest in biodiversity. Also, most datasets do not span the time it takes for nature to react to environmental changes (Estes et al., 2018). These issues create an integrative challenge because the collected data are highly heterogeneous, with variations in resolution, survey effort, species detectability, taxonomic focus and geographic and temporal scope often influenced by geographical, environmental and socio-political contexts. Further challenges include evaluating data completeness, quantifying sampling effort and assessing data quality (e.g. spatial/temporal uncertainty, species misidentification) and the complexity of conducting ground surveys, which are time-consuming and often hindered by the same geographical, environmental and socio-political contexts that influence data variability.

Biodiversity data are accumulating at an unprecedented pace from a diverse range of sources (Heberling et al., 2021). New technologies are increasingly being deployed, such as automatic sensors, eDNA, camera traps, satellite tracking and data mining from scholarly publishing. These techniques generate diverse data and data formats. Maximizing the utility of all this information requires integrating data across sources, including remote and in situ environmental data layers. To process these data, we need to escalate the development of tools and infrastructure for meaningful interpretations and deeper understanding. Too often, the results of biodiversity monitoring are incomparable or indistinguishable between time periods and regions (Gadelha et al., 2021; Valdez et al., 2023). There is also a considerable lag between the collection of biodiversity data and the conversion of those data into actionable knowledge (Dove et al., 2023; Groom et al., 2019; Gaiji et al., 2013).

Effective policy responses depend on swift and accurate biodiversity information. For instance, swift knowledge dissemination has proven important in addressing biodiversity-related disease outbreaks like Zika and Nipah viruses, aiding policymakers (Daszak et al., 2013; Keesing & Ostfeld, 2021). Similarly, reducing response time to biological invasions is vital for successful management (Kaiser & Burnett, 2010). Therefore, it is necessary that we develop a better and more efficient data landscape to enhance informed policymaking.

We envisage the rapid transformation of raw occurrence data into meaningful indicators, assessments and visualizations of biodiversity status and change. Moreover, this can be achieved with existing technology and frameworks (Dietze et al., 2018). Indeed, this ambition forms the basis for the EU-funded Building Biodiversity Blocks for Policy (B-Cubed) project. First, by using the *Essential Biodiversity Variable* (EBV) framework to develop analysis-ready datasets and integrating tools specifically designed for their use, we aim to lower existing barriers to extracting knowledge from raw data (Chatenoux et al., 2021; Giuliani et al., 2017). By chaining these tools together into automated *workflows*, we will provide regular outputs that are reproducible, open and useful. Second, we can take advantage of the flexibility, scalability and collaborative nature of *cloud computing* to make advanced data science techniques available to all. And finally, by developing the capabilities of the tools in close collaboration with *stakeholders*, we will greatly increase impact and expand the use of biodiversity information, smoothing the flow of information from primary data to decision-making (Figure 1).

Our aim here was to explain to a broad audience the project's aspirations. Ultimately, we want to contribute to the democratization of biodiversity data products globally, by building a community of decision makers, data scientists and software developers. We focused on species occurrence data to create adaptable workflows that not only lower the data processing, analytical and reporting burden of monitoring biodiversity for national, regional and global policy but also meet the changing needs of policy and assist continuous advances in data technologies and methods.

2 | BUILDING BLOCKS FOR BIODIVERSITY DATA

2.1 | Data cubes for assessing biodiversity change

To effectively convey global biodiversity status and trends, we need standardized variables that are clear to policymakers, reflect changes, include uncertainty estimates and encompass biodiversity's key aspects. The EBV framework allows for the communication of these parameters from complex datasets to decision-makers, preserving the data's detail and origin (Kissling et al., 2018; Pereira et al., 2013).

The most readily available data type for biodiversity are species occurrences (Gaiji et al., 2013). Occurrence records can be defined as objects in a three-dimensional space where the dimensions are taxonomic [what was observed?], temporal [when was it observed?] and spatial [where was it observed?]. For species distribution analysis, it has been proposed to create aggregated 'data cubes' of occurrence data (Kissling et al., 2018) for a range of analyses to indicate status and trends, and predictively model the future of biodiversity under different scenarios. Data cubes are not a new concept but were proposed to facilitate common operations on large datasets and to improve interoperability (Datta & Thomas, 1999). They have been adopted within the Earth Observation research community for data provision and analysis due to their ability to streamline spatial and temporal analysis workflows (Ferreira et al., 2020).

Data cubes are a powerful tool for organizing and analysing biodiversity data. These cubes are multidimensional structures where each dimension represents a variable of interest, such as species taxonomy, geographic location or time. Each 'cell' within the cube contains values or measures relevant to these dimensions. For instance, a biodiversity data cube could capture the presence of a species (taxonomy) at specific coordinates (space) and times (temporal dimension). This structure allows researchers to aggregate, compare and visualize data across multiple dimensions in a standardized and scalable way, facilitating communication for decision-making.

Data that conform to a single grid system are comparable, integratable and modelable. However, raw biodiversity observations rarely fit to the same geographic grid systems as environmental and landscape data (cf. data from remote sensing). A common solution is to reduce the resolution to a coarse grid. Such data are known as occupancy data (noting that technically occupancy depends on both the presence and detectability of an organism (MacKenzie et al., 2002)). Coarsening observational data inevitably leads to a loss of high-quality, fine-resolution data. It also introduces a bias as cells with a high population density are weighted equally to cells where the taxon is rare, resulting in a corresponding loss of sensitivity and resolution for indicators and models. To address this, algorithms can be used to convert raw biodiversity observations to a single high-resolution grid system (Groom et al., 2018; Oldoni et al., 2020). In doing so, we retain more of the available information.

Once created, a biodiversity occupancy cube can be further aggregated by any of its dimensions. The taxonomic dimension is hierarchical, allowing aggregation by higher taxonomy. For example, occurrence records from several species can be pooled together so as to perform genus-level analyses. In the biological processes that concern us, such as species distribution, temporal uncertainty is typically lower than the rate of change; therefore, a year is often a suitable aggregation span for many applications. These data cubes can be used to model future species distributions, generate indicators of biodiversity change, evaluate the status of biodiversity, improve monitoring and inform policy.

Cube generation is computationally demanding, but once created, they can be made individually referenceable with a digital object identifier. Such cubes can be bespoke, but can also follow a common parameterization so that they are comparable between regions. While many species distribution modelling and indicator workflows organize data into structures resembling data cubes, often through spatial and temporal binning, data cubes make this process explicit. This ensures that data can be consistently aggregated and analysed across workflows while maintaining clear metadata about the sources and transformations applied.

2.2 | Workflows

At their simplest, workflows involve collecting data on species occurrences and publishing them to platforms like GBIF, where the data are standardized to a common format and taxonomy. These standardized data are then harmonized onto a uniform spatial grid and combined with environmental variables. From this foundation, outputs can be produced such as maps, time series, predictive models and reports.

The EBV framework provides a strong foundation for biodiversity analysis and policy. However, it does not define the necessary computational and infrastructural requirements to achieve desired outcomes. For effective biodiversity information generation, we need repeatable Open Data workflows that transform primary data

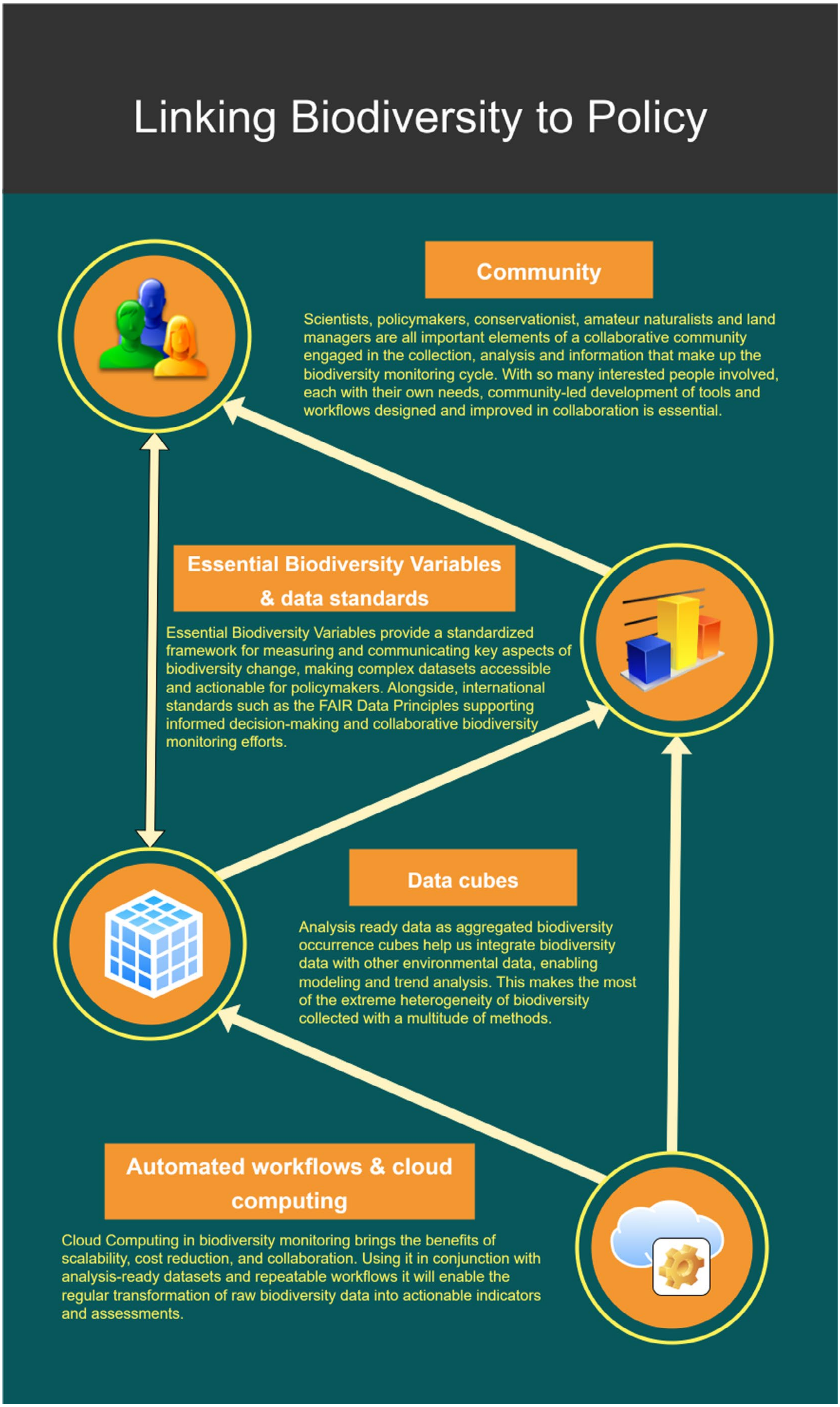
Linking Biodiversity to Policy
Community
Scientists, policymakers, conservationist, amateur naturalists and land managers are all important elements of a collaborative community engaged in the collection, analysis and information that make up the biodiversity monitoring cycle. With so many interested people involved, each with their own needs, community-led development of tools and workflows designed and improved in collaboration is essential.
Essential Biodiversity Variables & data standards
Essential Biodiversity Variables provide a standardized framework for measuring and communicating key aspects of biodiversity change, making complex datasets accessible and actionable for policymakers. Alongside, international standards such as the FAIR Data Principles supporting informed decision-making and collaborative biodiversity monitoring efforts.
Data cubes
Analysis ready data as aggregated biodiversity occurrence cubes help us integrate biodiversity data with other environmental data, enabling modeling and trend analysis. This makes the most of the extreme heterogeneity of biodiversity collected with a multitude of methods.
Automated workflows & cloud computing
Cloud Computing in biodiversity monitoring brings the benefits of scalability, cost reduction, and collaboration. Using it in conjunction with analysis-ready datasets and repeatable workflows it will enable the regular transformation of raw biodiversity data into actionable indicators and assessments.

FIGURE 1 The highly diverse biodiversity community is actively involved in every stage of monitoring and shaping policies related to biodiversity. Primary species observations are transformed to indicators through intermediate Data cubes following the Essential Biodiversity Variables framework. Each cube is independently referenceable and has the dimensions of taxonomy, time, and space. Using automated workflows, primary data are aggregated to a gridded occupancy cube and models are used to evaluate trends, project data and predict future scenarios. All indicators are created with measurements/indications of their uncertainty and all have sufficient metadata on provenance to be able to reproduce the result. The whole process occurs within a cloud-based architecture using internationally recognized standards. All components are open source, modular and configurable.

into clear, informative, and reproducible measures of biodiversity (Boyd et al., 2023; Groom et al., 2019; Seebens et al., 2020). To ensure transparency, reusability and sustainability, all inputs and outputs must adhere to the FAIR Data Principles. Embracing an Open Data—Open Source approach will allow the community to continuously scrutinize and repurpose workflows, and importantly enhance users' autonomy for updating and expanding datasets (Sica et al., 2024).

Biodiversity monitoring requires data management resources and informatics skills that can be costly—potentially a barrier to implementation for low- and middle-income countries. Standardized workflows that combine established data processing methods will allow anyone to adapt and run them for their country or region, making biodiversity assessment more consistent, accessible and cost-effective. This approach will lead to improved indicators of biodiversity change, reduced infrastructure costs and seamless integration of biodiversity data with other environmental factors.

Environmental data, such as those that are remotely sensed, are important covariates to occupancy data. They can be used, for example, to interpolate scattered field observations of biodiversity data (Cavender-Bares et al., 2022; Rocchini et al., 2022). The ready availability and seamless interoperability of data cubes encompassing both environmental and biodiversity variables significantly streamline the analysis process.

2.3 | Cloud computing

There is a growing need to move environmental data into cloud services where users can benefit from the following: (1) reduced costs; (2) outsourced maintenance, disaster recovery, security and loss prevention; and (3) a collaborative work environment and scalability (Meeus et al., 2022). The scalability of cloud computing reduces the computational barriers for analysing big data meaning that a wider array of models can be used, the spatial and temporal resolution can be increased and it is more adaptable to the user's needs. Furthermore, cloud computing can make collaboration possible that is otherwise difficult in siloed infrastructures. As such, this aligns with the strategic plan of GBIF, the single largest source of biodiversity data worldwide. In this plan they aim to *'include more and varied types of data and improved informatics services in order to supply the biodiversity information that global research and policy require'* (GBIF Secretariat, 2021).

2.4 | Connecting data to decision

Groom et al. (2019) advocate for biodiversity monitoring to be seen more as a community effort, with data cycles that motivate and reinforce that community. All stakeholders should be involved in the whole cycle and have tangible benefits from their contribution; otherwise, it is unreasonable to expect these disparate groups to cooperate towards a common vision. By (co-)developing data cubes and their associated workflows as tools to monitor trends and status of biodiversity, we can expect to close the gap between policy makers' needs, bioinformation specialists' skills and data collectors' motivations. Integration of proven but disconnected methods in biodiversity informatics and the simplification of access to, and deployment of, automated workflows on demand and automatically on a regular basis is timely and has been encouraged by many proponents (Jetz et al., 2019; Kissling et al., 2018).

To illustrate how our workflows and data cubes address real-world biodiversity challenges, we refer to the 'indicators' workflow developed by the TrIAS Project (https://github.com/trias-project/indicators). This workflow demonstrates how biodiversity indicators, such as trends in the introduction of non-native species in Belgium, can be calculated from occurrence data (Figure 2). By integrating raw species occurrence records into a standardized pipeline, it enables the production of actionable insights, including trend analyses and spatial visualizations, that directly inform national biodiversity strategies. Standardization simplifies data integration from multiple sources, ensures consistency across datasets and enhances interpretability for policymakers, making these outputs highly applicable to policy and management decisions.

In the TrIAS example, species occurrence data from more than 3000 datasets were aggregated and filtered to calculate temporal trends in the introduction of non-native species in Belgium. These aggregated trends were visualized and used to inform regional and national state of nature reports (e.g. Adriaens et al., 2020; Szczodry et al., 2020) and to develop policies for the national biodiversity strategy (Belgian National Focal Point to the Convention on Biological Diversity (Ed.), 2013). At the species level, temporal trends in high-impact species are informing risk management strategies in the Belgian regions, including specific approaches to reduce invasion impacts in protected areas in response to European regulation (D'hondt et al., 2022; Petersen et al., 2024). As all of these tools are open source, in collaboration with the responsible agency, a dashboard (https://radius-project.shinyapps.io/dashboard/) was set up which provides up-to-date information on invasive alien species

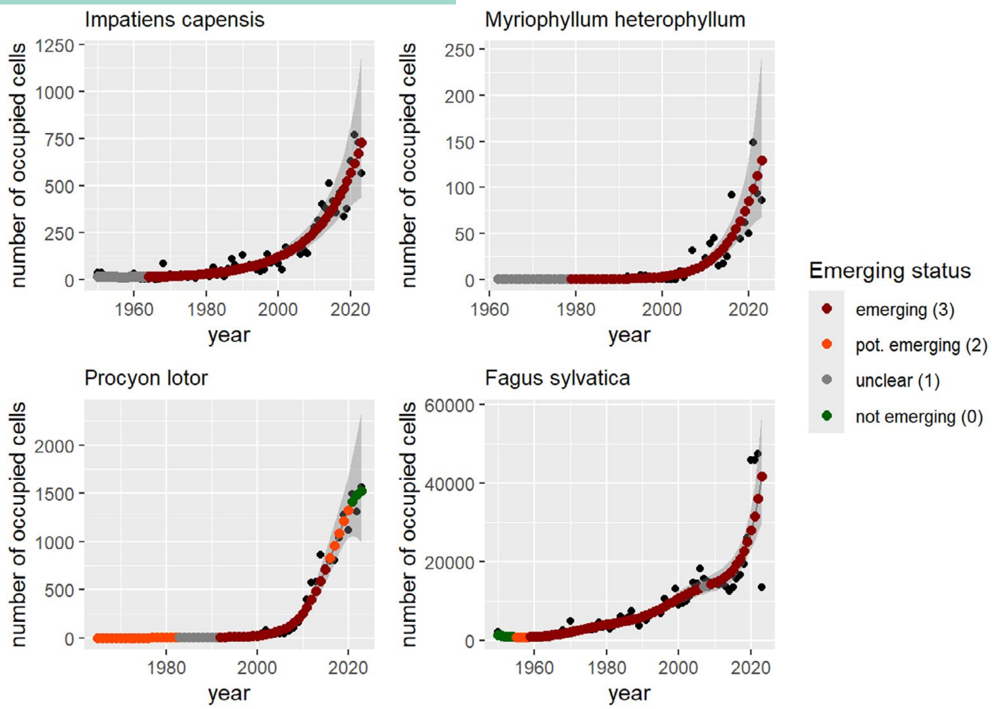

FIGURE 2 An example of a trend indicator for the occupancy of three non-native species in Belgium from 1950 to 2022 based upon a datacube built on 3124 datasets mobilized from GBIF (GBIF.Org User, 2025). *Pinus sylvatica* may be native to Belgium, but it has spread as a result of planting and the abandonment of marginal lands. The graphs show a modelled trend in the number of observations and the occupancy in Belgium. Black dots represent the number of occupied 1 km^2 cells, colours indicate emerging character of the species in any given year based on first and second derivatives of a fitted generalized additive model (GAM).

occupancy in protected areas such as NATURA2000 areas or nature reserves and, combined with spatial information on the occurrence of specific protected habitats, on the level of occupancy of these species in protected habitats.

There is a risk of oversimplification, potentially leading to the loss of important details. In a way of mitigation, rich metadata are associated with the data cube to facilitate interpretation, and expertise is necessary in the biology of organisms and the data collection processes to interpret results and to understand what steps should be taken to confirm important results.

Another need is the assessment of the most recent biodiversity datasets that can provide timely information on the increasing number of species required by EU regulations. On a recurring basis, Member States could benefit significantly from the integration of open datasets and the implementation of automated workflows at species level.

3 | DISCUSSION

Addressing and effectively managing the current biodiversity crisis requires that practitioners and policymakers have access to analysis-ready biodiversity data products that conform to open data principles and best practice information standards. B-Cubed, as a Horizon Europe-funded project, is developing such data products in the form of biodiversity data cubes, along with repeatable workflows that sufficiently document the process of cube creation. This allows comparability of analyses over space and time that can be rerun to react to changing needs and conditions. Such workflows also enable non-specialist practitioners to develop bespoke data products, should the provided data products not be fit for their purpose. By leveraging both the large amounts of biodiversity and environmental data that are being collected, aggregated and made available, along with advancements and availability in cloud-computing technology, B-Cubed aligns with the principles outlined in the Bari Manifesto for better data management and accessibility (Hardisty et al., 2019).

Despite the strengths and long-term benefits of the outlined vision, we recognize that implementing this vision requires overcoming multiple challenges. Automated workflows can save time and reduce errors, but they may require training or technical support for effective use. Moreover, input and output files need to follow established data standards and vocabularies (Hardisty et al., 2019; Pereira et al., 2022). Additionally, ensuring comparability in national and regional reports with previous years' data is crucial. This requirement can limit the adoption of new methods and workflows unless harmonization efforts are initiated early in the process.

In a cloud computing environment, it is an advantage if processes can be parallelized, though not all algorithms allow this approach (Cristobal-Salas et al., 2019).

It can be easy to treat biodiversity data as simply ones and zeros and then apply those data to mathematical and statistical models to produce an output. However, one needs to remember that these data represent complex and emergent biological entities. As such, processing biodiversity data involves domain-specific issues like different taxon concepts, data source diversity, unstructured error reporting, and the large range of biological traits. However, leveraging existing infrastructure like GBIF, which offers a common taxonomic backbone and data standards, makes the proposed approach viable. It also benefits from the expertise of communities like the Group on Earth Observation (GEO), GEO Biodiversity Observation Network (GEO BON) and regional bodies like the European Biodiversity Observation Network (EU BON).

Criteria for the success of B-Cubed will be measured by the adoption of common tools, services and products by decision makers and the data scientists who work with them. Sustainability is also a key aspect, which is why it is important to integrate environmental infrastructures globally. By making biodiversity monitoring more accessible to stakeholders, we will support global assessments of biodiversity and help countries deliver on policy targets. We see B-Cubed as a stepping stone to this vision. If you are working towards a similar vision, or perhaps feel we could support your goals in biodiversity monitoring, please get in touch.

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ACKNOWLEDGEMENTS

B^3 (Biodiversity Building Blocks for policy) receives funding from the European Union's Horizon Europe Research and Innovation Programme (ID No. 101059592). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the EU nor the EC can be held responsible for them. HT was funded by FCT-Foundation for Science and Technology, I.P., under the project CEECIND/08095/2022 and CESAM FCT/MCTES UIDP/50017/2020+UIDB/50017/2020+ LA/P/0094/2020. JRUW, SK, KTF and TZ thank the South African Department of Forestry, Fisheries, and the Environment (DFFE) for funding, noting that this publication does not necessarily represent the views or opinions of DFFE or its employees. DAC acknowledges support from the ARC SRIEAS Grant SR200100005 Securing Antarctica's Environmental Future. QG, TA, DO, TV and PD acknowledge the support of the Belgian Science Policy Office under the TrIAS project (BR/165/A1/TrIAS).

CONFLICT OF INTEREST STATEMENT

Tsungai Zengeya is an associate editor of Ecological Solutions and Evidence, but took no part in the peer review and decision-making processes for this paper.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/2688-8319.70113.

DATA AVAILABILITY STATEMENT

Figure 2 is based upon a GBIF download (GBIF.Org User, 2025) that has been made into a data cube and archived on Zenodo (Oldoni et al., 2024). Scripts used to generate the visualization are openly licensed on GitHub https://github.com/trias-project/indicators.

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How to cite this article: Groom, Q., Abraham, L., Adriaens, T., Breugelmans, L., Clarke, D. A., Di Musciano, M., Dove, S., Estupinan-Suarez, L. M., Faulkner, K. T., Fernandez, M., Hendrickx, L. A., Hui, C., Joly, A., Kumschick, S., Langeraert, W., Martini, M., Miller, J., Oldoni, D., Pereira, H., … Desmet, P. (2025). Creating the vision of rapid, repeatable, reactive data workflows for policy on biodiversity. *Ecological Solutions and Evidence*, *6*, e70113. https://doi.org/10.1002/2688-8319.70113