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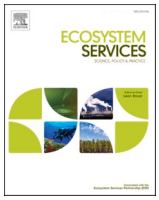

Full Length Article

Interoperability for ecosystem service assessments: Why, how, who, and for whom?

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A B S T R A C T

Despite continued, rapid growth in the literature, the fragmentation of information is a major barrier to more timely and credible ecosystem services (ES) assessments. A major reason for this fragmentation is the currently limited state of interoperability of ES data, models, and software. The FAIR Principles, a recent reformulation of long-standing open science goals, highlight the importance of making scientific knowledge Findable, Accessible, Interoperable, and Reusable. Critically, FAIR aims to make science more transparent and transferable by both *people and computers*. However, it is easier to make data and models findable and accessible through data and code repositories than to achieve interoperability and reusability. Achieving interoperability will require more consistent adherence to current technical best practices and, more critically, to build consensus about and consistently use semantics that can represent ES-relevant phenomena. Building on recent examples from major international initiatives for ES (IPBES, SEEA, GEO BON), we illustrate strategies to address interoperability, discuss their importance, and describe potential gains for individual researchers and practitioners and the field of ES. Although interoperability comes with many challenges, including greater scientific coordination than today's status quo, it is technically achievable and offers potentially transformative advantages to ES assessments needed to mainstream their use by decision makers. Individuals and organizations active in ES research and practice can play critical roles in creating widespread interoperability and reusability of ES science. A representative community of practice targeting interoperability for ES would help advance these goals.

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1. Introduction

1.1. The interoperability problem in ecosystem services

The amount of information, or knowledge (i.e., data, models, scenarios)[1] produced by scientists, practitioners, and citizens continues to increase rapidly, yet too often remains compartmentalized and sees limited reuse, failing to produce collective knowledge (Nelson, 2009, Nesic et al., 2011, Munafo et al., 2017, Balbi et al., 2022). This is particularly true for studies of ecosystem services (ES), which depend on the integration of knowledge from a range of disciplines to understand complex, linked human-natural systems (Rieb et al., 2017, Carmen et al., 2018, Schmidt and Seppelt, 2018). Data used and produced in ES research are acquired and generated using diverse approaches. This plurality reflects the interdisciplinary nature and richness of the field. At the same time, knowledge can only grow and evolve through effective sharing and reuse. As scientific literature grows far faster than individual scientists can assimilate (Borycz and Carroll 2020) and researchers seek to provide timely, accurate, decision-relevant ES monitoring (Vaz et al., 2021; Balvanera et al.., 2022; Gonzalez et al., 2023a), solutions to effectively integrate and reuse knowledge are needed.

The FAIR Principles (Wilkinson et al., 2016, 2018; Lamprecht et al., 2020, Barker et al., 2022; see Box 1 for acronym definitions and Box 2 for definitions) mandate that modern scientific data, models, and software be Findable, Accessible, Interoperable, and Reusable to both human users and machines. These principles have gained increasing recognition and application as a useful reformulation of long-standing open science goals supporting trust and reproducibility (Powers and Hampton, 2019). Specifically, the FAIR Principles call for data, models, and software that are *findable* and *accessible* on the internet, integrated with other independently produced knowledge seamlessly and without compatibility issues (*interoperable,* see Section 2), and effectively recombined or replicated in new applications (*reusable*). Critically, scientific knowledge is not dualistically classified as FAIR versus not FAIR. Rather, knowledge can be more or less FAIR, and any improvements in FAIR science are beneficial.[2]

It is important to precisely define interoperability, since multiple definitions exist (IEEE, 1990, Heiler, 1995, Wang et al., 2009, Lamprecht et al., 2020). In this paper, we use definitions from Heiler (1995), who distinguishes between *syntactic interoperability* – the use of compatible data formats and digital communication protocols – and higher-level *semantic interoperability* – data transfers where a receiving system correctly identifies the meaning of exchanged data, reusing it appropriately (see also Guizzardi, 2020).

Modern data and code repositories typically support findability and accessibility, but interoperability and reusability – particularly for machines – cannot be reached solely through the adoption of repositories (Borycz and Carroll, 2020, Papoutsoglou et al., 2023). For example, a recent IPBES global model intercomparison quantifying past and future changes in biodiversity and ES (Kim et al. 2018, Rosa et al. 2020, Pereira et al. 2024) illustrates current best open-science practices. This extensive effort used public code and data repositories (GEO GEO BON, 2024a) and community-developed metadata (GEO GEO BON, 2024b), greatly improving its compliance with the FAIR Principles. However, the integration of this work with other independently produced ES data and models remains a highly technical, time-consuming endeavor, illustrating incomplete achievement of high-level interoperability (see section 2).

The high disciplinary and methodological diversity of ES poses particular challenges for achieving interoperability. This makes the FAIR Principles' calls for community standards challenging. Disciplinary diversity means that data types and the concept of "data" itself varies between fields. The contribution of social sciences, particularly through participatory methods (Krasny et al., 2014, Ramirez-Gomez et al., 2015, Ausseil et al., 2022), has advanced the ES field considerably, but often produces qualitative data for which metadata standards remain elusive. Additionally, including diverse indigenous perspectives, which is both scientifically essential (Stoeckl et al., 2021, Kobluk et al., 2024) and required by international conservation agreements (CBD, 2022a), requires reevaluation of what constitutes data (Walter and Suina, 2019). Such cases pose particularly difficult challenges in achieving community standards aligned with the FAIR Principles.

Further, there are cases where conceptually flexible definitions of ES concepts can be considered beneficial, rather than a challenge to be overcome. Steger et al. (2018) elaborate on the benefits and drawbacks of making ES more standardized versus intentionally vague and flexible. We believe that the application of precise and rigorous *semantics*, which formalize meanings using logic, for *quantitative ES assessment* (see section 1.2) can coexist alongside *pluralistic definitions* for contested aspects of "ES value" (Wallace and Jago, 2017, Jax et al., 2018, Wallace et al., 2020), particularly by recognizing non-western worldviews (e.g., indigenous and other local perceptions of ES), which can improve representation, equity, and comprehensiveness in ES assessments (de Valck et al. 2023).

Wider understanding, consensus, and application of interoperability to ES offers numerous benefits (see sections 3.5 and 5.3). Interoperability is essential for addressing complex multiscale challenges, where multiscale scientific knowledge is needed to inform coherent decisions by nested governance levels. Today's sustainability challenges require timely, versatile, and easy-to-produce knowledge to support global targets and policy goals (Balbi et al., 2022, COP28, 2023). Interoperability is thus an important prerequisite to mainstreaming the production of ES information to inform policy at all levels of decision making. Solutions to the interoperability problem need to be developed, endorsed, and applied by the broad research community; doing so enables the field to advance in ways that isolated individuals and research groups cannot. Widespread achievement of interoperability in ES will likely require the efforts of a dedicated and representative community of practice, making greater awareness of the topic timely.

1.2. The semantics challenge

Interoperability for ES requires (1) the consistent use of approaches enabling software to seamlessly exchange data, e.g., using open and cloud-optimized file formats and well-documented and community-endorsed application programming interfaces (APIs) (see section 2) and (2) consistent semantics to describe scientific data and models so that they can be understood by both people and machines (see section 2.1). The semantics challenge is greater for a disciplinarily and conceptually diverse field like ES.

[1] We use the term "knowledge" in reference to scientific data and models, recognizing that data and models embody statements of scientific knowledge (Villa et al., 2009).

[2] For a short, humorous perspective on the consequences of ignoring the FAIR Principles, see Hanson et al. (2012).

Box 1
Definitions of acronyms.

AI – Artificial Intelligence
API – Application Programming Interface
ARIES – Artificial Intelligence for Environment and Sustainability
BFO – Basic Formal Ontology
CARE – Collective benefit, Authority to control, Responsibility, Ethics
DOI – Digital Object Identifier
DOLCE – Descriptive Ontology for Linguistic and Cognitive Engineering
EBV – Essential Biodiversity Variable
EESV – Essential Ecosystem Service Variable
ENVO – Environment Ontology
ES – Ecosystem Services
ESTIMAP – Ecosystem Services Mapping Tool
FAIR – Findable, Accessible, Interoperable, Reusable
GBiOS – Global Biodiversity Observation System
GEO BON – Group on Earth Observations Biodiversity Observation Network
I-ADOPT – InteroperAble Descriptions of Observable Property Terminology
INCA – Integrated System for Natural Capital Accounting
INSPIRE – Infrastructure for Spatial Information in the European Community
InVEST – Integrated Valuation of Ecosystem Services and Tradeoffs
IPBES – Intergovernmental Science-Policy Panel on Biodiversity and Ecosystem Services
k.LAB – Knowledge Laboratory
ORCID – Open Researcher and Contributor Identifiers
PURL – Persistent Uniform Resource Locator
SEEA – System of Environmental-Economic Accounting
SEEA EA – System of Environmental-Economic Accounting Ecosystem Accounting
TRUST – Transparency, Responsibility, User focus, Sustainability, Technology
URL – Uniform Resource Locator

Box 2
Definitions of key terms.

Application programming interface (API): a set of software protocols that enables two applications to exchange information.

Artificial Intelligence (AI): the science and engineering underlying the development of intelligent machines, especially computer programs or robots. AI encompasses approaches including machine reasoning, semantic annotation, machine learning, and others (see Russell and Norvig, 2020).

CARE Principles: Principles for Indigenous Data Governance (Carroll et al., 2020), encompassing:

Collective benefit: benefits "for Indigenous Peoples to achieve inclusive development and innovation, improve governance and citizen engagement, and realize equitable outcomes."

Authority to control: Indigenous determination of "data governance protocols (and)… stewardship decisions for Indigenous data that are held by other entities."

Responsibility: by non-Indigenous researchers to "nurture respectful relationships with Indigenous Peoples from whom the data originate… (including) investing in capacity development, increasing community data capabilities, and embedding data within Indigenous languages and cultures."

Ethics: accounting for Indigenous rights and wellbeing "to minimize harm, maximize benefits, promote justice, and allow for future use."

Classification/typology: The organization of elements by grouping them together in mutually exclusive classes based on shared properties or other parameters.

Concept: Abstractions, i.e., describing a class/type, that represent instances of an entity. This is a very general definition of "concept," for further detail, see Margolis and Laurence (2023).

Containerization: the integration of computer code with all necessary software dependencies and operating system, which enables it to be executed in an isolated manner on any computer system.

Controlled vocabulary: a set of predefined terms to describe information, allowing for its retrieval.

Crosswalk: Practices to facilitate translation between different semantic resources (e.g., classifications).

Decision rule: In the context of this paper, the specification of appropriate conditions under which scientific knowledge about ES can effectively be reused, expressed in a human- and machine-readable manner. Decision rules can act as guardrails against the improper reuse of knowledge.

Definition: The meaning of a certain entity (a simplified definition; for further detail, see Gupta and Mackereth, 2023).

Ecosystem service accounting: for the purpose of this paper, approaches that use accounting rules to structure information on ES (e.g., U.N., 2021).

Ecosystem service assessment: for the purpose of this paper, studies that quantify ES in relative, physical, and/or monetary terms using qualitative, semiquantitative, or quantitative methods.

Ecosystem service monitoring: for the purpose of this paper, approaches that use repeated measurement or modeling of ES to track changes in ES over time.

FAIR Principles: guidance for the curation, management, and reuse of scientific data, models, software, and workflows understandable for humans and machines, encompassing:

Findability: the ability to locate or discover, scientific knowledge by humans or machines**.**

Accessibility: the ability to access scientific knowledge, "possibly including authentication and authorization" (GO FAIR, 2024).

Interoperability: "the ability of data or tools from independent resources to integrate or work together with minimal effort (Wilkinson et al. 2016). Interoperability can be achieved with compatible data formats and communication protocols (syntactic interoperability) or data transfers where a receiving system can properly identify the meaning of exchanged data, reusing it appropriately (semantic interoperability, (Heiler 1995))." (Balbi et al., 2022)

Reusability: the ability to enable scientific knowledge to be "replicated and/or combined in different settings" (GO FAIR, 2024).

Inference: the use of evidence to draw a conclusion.

Knowledge base: any machine-readable collection of annotated and organized information, which can include semantics as applied to data, models, and associated scientific knowledge (Villa et al., 2009).

Knowledge engineering: an AI field dedicated to the representation, management, and adoption of knowledge.

Machine actionability: "information that is structured in a consistent way so that machines, or computers, can be programmed against the structure" (DDI DDI Alliance, 2024). Often interpreted as the use of FAIR knowledge by machines and used synonymously with "machine readability."

Machine learning: the use of various algorithms to uncover patterns (e.g., regression, classification, or clustering) in large datasets. Machine learning is currently the most widely used form of AI (see Mitchell, 1997).

Machine reasoning: (i.e., machine-operated logical inference using formalized semantics): "applied to a semantically annotated knowledge base, machine reasoning can support automated validation and linking of data and models using logic to assemble them into useful structures for computation. Reasoning systems can tackle new problems and build higher-level knowledge using deductive and inductive reasoning." (Balbi et al., 2022)

Ontology: systematic descriptions of concepts, entities, and relationships between them, which are logically consistent and fully descriptive.

Domain ontology: ontologies representing relevant elements of a specific scientific field (e.g., hydrology, economics, biology).

Core ontology: "mid-level ontologies" that serve as a conceptual bridge between upper-level ontologies and multiple domain-specific ontologies (Obrst, 2010).

Upper-level ontology: a domain-independent ontology that defines the most general entities (e.g., events, processes, time, space) and relationships between them. Typically, upper ontologies assume a specific philosophical view on reality and the elements composing it. Examples of upper-level ontologies are BFO (Otte et al., 2022) and DOLCE (Borgo et al., 2022).

Persistent identifier: an enduring reference to a person, publication, webpage, or other entity, as opposed to references that may change frequently, such as some internet Uniform Resource Locators (URLs). Examples include Digital Object Identifiers (DOI), Persistent Uniform Resource Locators (PURLs), and Open Researcher and Contributor Identifiers (ORCID).

Provenance: in the context of semantic technologies, provenance refers to the origin of information describing how it is created, stored, and modified (see W3C, 2010).

Semantics: the attribution of meanings to words or expressions. Semantics often refer to the formalization of meanings in terms of logical declarations and axioms, sometimes translated into formal ontologies (which define concepts and the relations between them), breaking meanings into modular components. "Semantic annotation can label scientific data and models with well-defined categories linked by clearly bounded logical relationships and can play a key role in knowledge integration" (Balbi, 2022).

Thesaurus: a set of terms organized to describe narrower and broader concepts, as well as synonyms and translations between different vocabularies (see Obrst, 2010).

Taxonomy: a set of concepts hierarchically organized to express parent–child relationships (Obrst, 2010).

Version control: "the practice of tracking and managing changes to software code," (Atlassian, 2024) which can be applied to both scientific software and model code.

Web Services: a set of software protocols that enable two machines to exchange information over a network. Open Geospatial Consortium Web Services support automated spatial data access and processing.

Prominent historical cases where scientific terms and meanings were standardized include the introduction of the periodic table, which identified chemical elements and their relationships by families, and Linnaean taxonomy, which identified species and their interrelationships through higher-level taxa. These systems replaced inconsistent worldviews in chemistry and biology, giving scientists standardized language and predictive models to further test and refine. New discoveries conformed to an agreed terminological and logical structure – standardized concepts for chemical elements and species and the relationships between them.

More recently, substantial efforts toward interoperability have been critical for supporting intercomparison of climate (Edwards, 2011) and agricultural models (AgMIP, 2024), and are also needed to support geospatial mapping and modeling (Fischer et al., 2023, Strobl et al., 2024). Other fields of science, most notably genetics (Gene Ontology Consortium, 2019) and biomedicine (Jackson et al., 2021), but more recently the geosciences (Gil et al., 2019, Zhang et al., 2019, Tucker et al., 2022), have made substantial advances toward more widespread interoperability and reuse. For example, the use of common file formats, scientific repositories, metadata standards, including common ontologies and controlled vocabularies, and informatics tools and pipelines, have enabled vast, synthetic advances in the field of genomics (ICGC/TCGA Pan-Cancer Analysis of Whole Genomes Consortium, 2020). Bada et al. (2004) note that seven characteristics contributed to the successful application of semantics in the genomics community: "community involvement; clear goals; limited scope; simple, intuitive structure; continuous evolution; active curation; and early use."

The above subjects entail fewer disciplines and system parameters than the ES field. Despite these differences, improved standardization for quantitative ES assessments could produce more interconnected, efficient, and effective science. ES researchers have recognized the need for metadata standards (Crossman et al., 2013), spatial data repositories (Drakou et al., 2015), and open science-focused publishing outlets (Burkhard et al., 2016). Beyond these early efforts, the field has generally lagged in the implementation of standards that could support interoperability, though some recent overview papers have recognized the problem (Schmidt and Seppelt, 2018, Drakou et al., 2019, Finisdore et al., 2020).

This paper addresses the semantics challenge, including "why, how, who, and for whom" questions of interoperability for ES – why does interoperability matter, how can it be achieved, whose involvement is needed, and who benefits from its widespread implementation? We focus on quantitative ES assessments[3] using primary data or computational modeling to produce biophysical and/or monetary estimates, although interoperability may also be relevant for semi-quantitative data and models. We discuss progress and potential for interoperability through the lenses of three major international ES-relevant initiatives – IPBES (IPBES, 2022a), SEEA (U.N. et al., 2014; U.N., 2021), and GEO BON (Vaz et al., 2021; Balvanera et al.., 2022) and for more localized ES assessments. We also recognize the importance of addressing interoperability in adjacent fields such as Earth observation and sustainability science (Balbi et al., 2022, Mazzetti et al., 2022, COP28, 2023).

2. Interoperability basics for ecosystem services

Since ancient times, humans have adopted strategies to organize and structure knowledge. These include systems of categories and classifications (i.e., lists of general entities, kinds, or classes representing aspects of the world (Thomasson, 2022)), which can serve as conceptual tools for defining terms and concepts with precise meanings.,[4][5]

[3] We use the term "ES assessment" for studies quantifying ES in relative, physical, and/or monetary terms; "ES monitoring" for approaches using repeated measurement or modeling to track changes in ES over time; and "ES accounting" for approaches using accounting rules to structure information on ES (e.g., U.N. 2021). ES modeling is frequently used in all three types of studies.

[4] In this article, we will not touch upon the meanings of meaning and their relation with words and concepts, which have already been the subject of multiple articles, for example, collected in the Stanford Encyclopedia of Philosophy (Zalta and Nodelman, 2024).

[5] In addition to the field of philosophy, research in cognitive science, semantics and psychology offer significant contributions to the study of concept representation and categorization. Some borrow ideas from the Aristotelian tradition, while others are inspired by psychology, for example prototype theory, which stresses how natural categories and the characteristics which define them play a role in concept categorization (Margolis and Laurence, 2023).

Aristotle's categories and metaphysics (Thomasson, 2022) have inspired many more recent knowledge architectures (Smith, 2023). As scientific disciplines evolved and intertwined, several frameworks and interpretations have emerged to support analysis and understanding, a trend that continues in the field of ES. A multitude of perspectives brings some benefits to scientific interpretations, yet plurality also creates challenges, for example the tracking of differences and similarities among terminologies and definitions, conceptualizations, and frameworks (Adamo and Willis, 2022). Interdisciplinary fields in particular are exposed to the use of ambiguous semantics, such as using different words to describe the same concept or the same word to describe different concepts (Dini et al., 2011, Laniak et al., 2013, Bull et al., 2016). Such semantic ambiguity complicates the achievement of interoperability and reusability.

Some of these issues can be addressed through use of community-endorsed, standardized vocabularies to define metadata (see FAIR Principles I2, I3, R1.3, Wilkinson et al. 2016). This enables multiple researchers contributing compatible data or models to ensure they are describing the same entities, supporting their correct reuse by people or machines (e.g., NLM, 2019 for health data).

Along with the more significant "semantics challenge," for which widespread consensus does not yet exist, various technical prerequisites are needed to support interoperability for ES. Prerequisites include the use of standardized, well-documented protocols for information exchange (i.e., APIs), open, machine-actionable file formats (e.g., STAC, 2024), and appropriate licensing for data and software/model code. Although the importance of these prerequisites is well-recognized by open-science advocates (Wilkinson et al., 2016, Lamprecht et al., 2020, Barker et al., 2022), further work is needed to improve their adoption in the ES community since their application is not yet universal. In this section, we describe basic principles needed to support interoperability in an interdisciplinary field like ES, starting with semantics (see further detail elsewhere (Gruber, 1993, Smith et al., 2007, Guarino et al., 2009, Antoniou et al., 2012, Janowicz et al., 2015, Guizzardi, 2020)).

2.1. Semantics: from consistent concept definitions to machine-readable knowledge

As previously noted, semantics representing scientific knowledge begin with clear, unambiguous definitions of concepts. Certain concepts can be organized into *classifications* or *typologies* – specialized lists that must be exhaustive and mutually exclusive (e.g., La Notte and Rhodes, 2020). Concepts can also be aggregated into *glossaries* or more structured *controlled vocabularies*, which collate standardized terms, and are often developed by individual scientific disciplines (e.g., Potschin-Young et al. 2018). Controlled vocabularies can enable efficient searching, information retrieval, and interconnection of data and models (Davies, 2010). They support, for example biodiversity science and monitoring (Wieczorek et al., 2012; Guralnick et al., 2018) and model integration within large collaborative Earth science projects (Zhang et al., 2019; Tucker et al., 2022). *Thesauri* can supply synonyms and translations between different vocabularies, and *crosswalks* can enable translations across different classification systems (e.g., U.N., 2021).

Beyond controlled vocabularies, *ontologies* (Gruber, 1993; Guarino et al., 2009) add formal logical structure to systematically and completely describe relevant relationships, rules, and restrictions between concepts, facilitating deeper information interpretation. Common examples describe hierarchical relationships like parent–child classes and logical restrictions that associate properties with concepts. For example, the thesaurus definition of a "natural hazard" concept (UNESCO, 2022) could include a range of related concepts (e.g., "disaster," "flood," and "damage"). By contrast, a formal ontology can express that "fluvial flooding" and "drought" are disjoint child classes of "natural hazard" and that "fluvial flooding" is caused by "precipitation" "exceeding" "soil infiltration capacity.".

Ontologies are ideally shared by the research community, as the product of consensus (Studer et al., 1998, Neuhaus and Hastings, 2022). This is usually easier to achieve in small, single-discipline research communities (e.g., Gene Ontology Consortium, 2019, Taylor et al., 2019). In an interdisciplinary field like ES, a more realistic goal may be to find practical and consistent definitions that are still recognizable by the community. Doing so requires collaboration between a diverse range of stakeholders, including disciplinary scientists, policy makers, community members, *knowledge engineers* who are experts in semantics and knowledge representation,[6] and facilitators.

To improve efficiency and trust, ontologies ideally reuse knowledge from preexisting, community-endorsed ontologies. However, ontologies encode assumptions about their view of the world using formal logic, and logical inconsistencies can pose serious problems for their use by machines. It is also valuable to keep ontologies parsimonious, by only including necessary elements, since larger, more complex ontologies are harder to maintain and reuse. In practice, in order to maintain logical consistency and parsimony while ensuring availability of needed

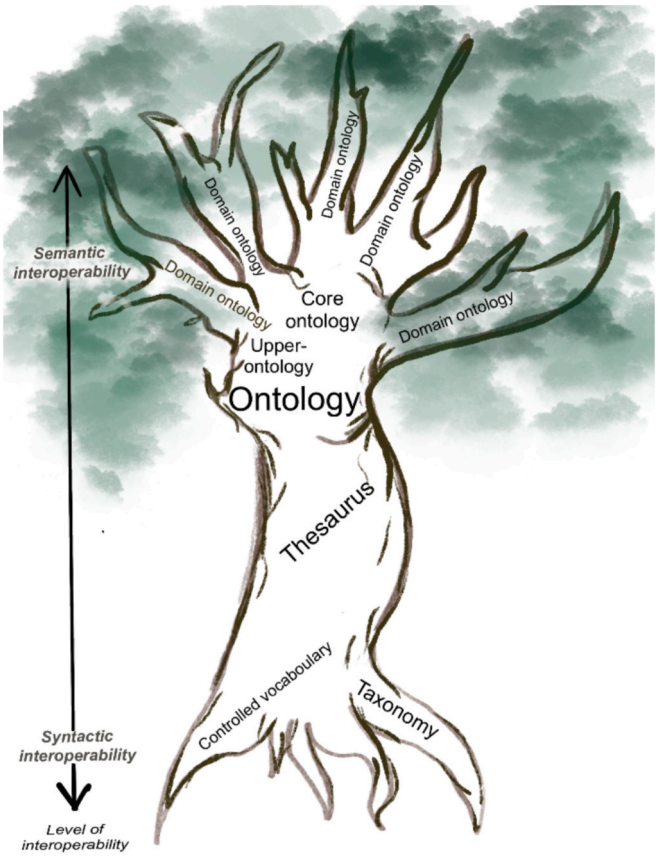

Fig. 1. Simplified overview of how different semantic resources can enable interoperability in interdisciplinary fields like ecosystem services, describing scientific entities and relationships in a machine-actionable way. The roots (representing simpler syntactic interoperability) and branches (representing semantic interoperability) illustrate the need for multiple, often discipline-specific, taxonomies or controlled vocabularies (for syntactic interoperability) or domain ontologies (for semantic interoperability) to define needed scientific entities. Taxonomies and controlled vocabularies can be linked using thesauri or crosswalks. When applied to an interdisciplinary field like ecosystem services, domain ontologies strongly benefit from connections to shared core and upper-level ontologies. This image is a re-adaptation of similar images produced by the scientific community, e.g., by Obrst (2010).

[6] Knowledge engineers are interdisciplinary professionals who design and develop systems that capture, formalize, and structure knowledge, creating and maintaining ontologies (Neuhaus et al., 2011).

concepts, existing ontologies are often reworked rather than directly reused (best practices exist for doing so; Fernández-López et al., 2019, Haller and Polleres, 2020). These challenges suggest the need for coordination across the ES community to come to consensus on and use of shared semantics, rather than having multiple "competing standards" emerge, which would undermine interoperability goals.

Effective metadata describe both the entity under consideration and its measurement characteristics (e.g., continuous or categorical, ranking or measurement, measurement units; Crossman et al 2013). These details typically require alignment of *domain ontologies* (for specific disciplines, e.g., economics or hydrology) with *upper-level* or *core ontologies* that describe domain-independent aspects of scientific entities (Fritzsche et al., 2017; Fig. 1), such as BFO (Otte et al., 2022) or DOLCE (Borgo et al., 2022). As an interdisciplinary science, ES researchers must use semantic resources capable of navigating across disciplines (Fig. 1, see section 3.1). While detailed, standardized metadata describing the content of ES data and models are essential, so is consensus on what the "entity under consideration" is, which terms describe the entity, and critical evaluation of whether commonly used representations (indicators) describe what is meant by the concept (i.e., "indicator-indicandum fit," without which error can readily arise, Heink and Kowarik, 2010, Wallace and Jago, 2017).

The logical formalization of scientific concepts enables inference – i.e., using evidence to draw conclusions. People use logical inference constantly, for example by reading today's weather forecast before deciding what to wear outdoors. Through *machine reasoning* (like ontologies and machine learning, a subfield of artificial intelligence), computers can logically infer relationships and flexibly connect information (Janowicz et al., 2015). This enables, for instance automated coupling of two models or substitution of one dataset, model, or model parameterization for another. A computer system capable of machine reasoning can respond to scientific questions requiring the use of different data, models, and model parameterizations (Villa et al., 2009), rather than solely by retrieving facts. This approach has transformative potential for using data and models to produce ES assessments.

3. Current and emerging solutions for interoperability in ecosystem services

3.1. Relevant semantic resources

The need for shared language and meanings to describe scientific data and models is readily evident in any project involving large-scale data collection, interdisciplinary modeling, or knowledge synthesis (e.g., IPBES' activities, section 4.1). For instance, controlled vocabularies are used to support syntactic interoperability for long-term ecological research (Mirtl et al., 2018), cataloging of ES models (USEPA, 2019), and Earth sciences model integration (Tucker et al., 2022). However, such approaches cannot support semantic interoperability, which requires use of ontologies that enable machine reasoning (Guizzardi, 2020).

A range of biological and ecological ontologies support interoperability (e.g., Ison et al., 2013, Lannom et al., 2020, Maganga et al., 2021). The BFO-grounded ENVO ontology (Buttigieg et al., 2013) is often used to represent ecological entities. Semantic resources for areas related to ES address social-ecological systems (van der Werf et al., 2009; Adamo and Willis, 2022), agroecosystem services (Martin-Clouaire, 2018), land use (Fischer et al., 2023), and life-cycle assessment (Ghose et al., 2022). To our knowledge, these resources have seen limited use in supporting ES data and model interoperability. Lastly, the ESOnto (Ayuningsih, 2019, Drakou et al., 2019) and ESMO ontologies (Affinito et al., 2024) are specific to ES (see section 4.3).

The I-ADOPT framework for biodiversity data (Maganga et al., 2021), Scientific Variables Ontology (Stoica and Peckham, 2019), the Artificial Intelligence for Environment & Sustainability (ARIES) project's Ontology of Descriptions and Observations for Integrated Modelling (Villa and Adamo, 2024), and best practices proposed to support the European Union INSPIRE Directive (Leadbetter and Vodden, 2016, INSPIRE, 2024) share substantial conceptual overlap. Specifically, they share four common characteristics: (1) reliance on both discipline-specific domain ontologies and a core/upper level ontology describing scientific observations and measurements; (2) use of atomic concepts to build more complex ones; (3) the requirement that both an entity and a property being measured must be combined to produce a complete scientific observation (e.g., not just "land surface" but "land surface temperature in °C"); and (4) the ability to describe roles, measurement methods, and matrices or realms in which measurements took place. These characteristics suggest a path toward supporting interdisciplinary semantic interoperability through full expressivity, logical consistency, parsimony, and reuse of existing semantic resources.

3.2. Interoperability for ecosystem services models and software

Scientific models and computational workflows should support interoperability (Goble et al., 2020) and, like most fields, the boundary between modern ES models and software is blurry. ES models range from qualitative to quantitative and from one-off, bespoke methods to repeatedly applied approaches (Palomo et al., 2017). The path to interoperability and the benefits of achieving it differ for such approaches. Repeatedly used quantitative models (e.g., ESTIMAP, Zulian et al., 2018, InVEST, Natural Capital Project, 2024) may be suitable for improved reusability and interoperability, if modelers make underlying data, models, and model parameterizations machine actionable, semantically annotated, and/or specify appropriate conditions for reuse (see section 3.4).

Reuse of knowledge from semi-quantitative approaches using public, stakeholder, or expert judgment (e.g., Semmens et al., 2019, Campagne et al., 2020) may be possible with great care. Such reuse requires careful attention to the ecological and socioeconomic context of past studies and their data, methods, and surveyed populations. Knowledge reuse from such studies may provide a useful starting point for stakeholder deliberations in new contexts, rather than a final answer to questions in new settings. By contrast, qualitative ES data are likely to be more difficult to reuse. Place-based and qualitative assessments can be highly useful for supporting participatory processes and providing inputs to decision making (Potschin and Haines-Young, 2013). However, highly tailored assessments built using public, indigenous, and/or expert knowledge may simply not be transferrable to other contexts, particularly when reflecting unique individual or community values.

Software interoperability is complex, as it must interact with other software, data, and computational environments. FAIR Principles for research software thus reflect needs to ingest, operate on, exchange, and output FAIR data (Lamprecht et al., 2020, Barker et al., 2022). Use of standardized protocols for information exchange (i.e., APIs, data formats, libraries, and software registries) can contribute to software interoperability (Lamprecht et al., 2020, their Fig. 1). While data can be made more FAIR at the end of its production process, there are advantages to working toward FAIR software from the beginning – for example, it can be more efficiently reused by others even while in development (Barker et al. 2022).

Buchhorn et al. (2022) show how to assess adherence of ES software to the FAIR Principles, based on the INCA ecosystem accounting tool. Creation of this tool entailed harmonization and recoding of the European Union Joint Research Centre's ES models (Zulian et al., 2018), their pairing with analysis-ready data, automation of geospatial operations, and metadata enrichment. At the time, the INCA tool fully met eight of 15 FAIR Principles for software and six of 15 FAIR Principles for data, with interoperability being the least well-attained principle. Recently, substantial progress has been made in making the INCA tool interoperable with ARIES, which operates on and produces FAIR input and output data, an important consideration for FAIR software (see Box 3).

3.3. Navigating data/model reuse through "guardrails"

A shared *knowledge base* for ES can grow through the contribution of new FAIR datasets and models, but also through machine-readable *decision rules* about where and how to reuse them (Moon et al., 2017, Spake et al., 2019; FAIR Principle R1). Such decision rules can describe fitness for purpose of data and models, building guardrails against their improper reuse, particularly in automated workflows. Fitness for purpose descriptions are typically found in literature reviews and the discussion sections of papers describing data or models.

For example, a researcher could use well-defined, shared semantics to specify that a particular model, dataset, or parameterization is appropriate to reapply in a particular context – i.e., for a given ecoregion or climatic zone,[7] in urban ES assessments for cities of a given size or socioeconomic status, or for assessments taking place at a particular spatiotemporal scale (Benavidez et al., 2018; Leyk et al., 2019; Martínez-López et al., 2019). Such decision rules can be perused by algorithms to choose the most appropriate knowledge to address a problem in a specific context. Full descriptions to support proper reuse may also include information about instrumentation, observation conditions, data collection protocols, data processing, provenance, and original research purpose (Gregory et al., 2019; FAIR Principles R1/R1.2). Further research is needed into how to more systematically describe data and models' fitness for purpose using semantics.

3.4. Reducing heterogeneity in ES definitions – From taxonomies to logic-driven semantics

Substantial semantic debate has focused on the question of "what should we call ES?," through distinct classifications (e.g., Millennium Ecosystem Assessment, 2005, La Notte and Rhodes, 2020), which has more recently evolved into the question of "how can we conceptualize diverse human-nature relationships?" (Chan et al., 2016, Pascual et al., 2017, van Riper et al., 2017, Saxena et al., 2018).[8] Earlier calls for increased interoperability in ES largely addressed these classification questions (Drakou et al., 2015, Palomo et al., 2018, Ayuningsih, 2019), with less focus on the application of semantics to support data and model interoperability. However, ontologies can go beyond crosswalking approaches (e.g., U.N., 2021) to address longstanding ES classification challenges, more precisely defining ES to minimize category mistakes (Wallace and Jago, 2017).

For example, certain models define "pollination services" differently, precluding direct comparison (Rosa et al., 2020). These authors noted that "while GLOBIO-ES… defines pollination services as 'the fraction of cropland potentially pollinated, relative to all available cropland', InVEST defines it as 'the proportion of agricultural lands whose pollination needs are met'… although similar in definition, mathematically these were calculated very differently… making their direct comparison unfeasible." Rosa et al. (2020) manually harmonized these metrics and compared their proportional changes across studies, but could such a process be automated? By encoding these definitions in a machine- and human-readable manner, we can lay the foundation for improved intercomparison of model results by machines. For example, using the atomic concepts found in ARIES' ontologies, the GLOBIO-ES (1) and InVEST (2) pollination services can be defined in a human- and machine-readable manner as follows:

(1) im:Proportion of im:Potential agriculture:Pollinated landcover: Cropland.
(2) im:Proportion of im:Realized agriculture:Pollinated landcover: AgriculturalVegetation

In this case, im refers to ARIES' core ontology (containing generalized scientific measurement concepts like "Proportion" and "Potential" vs. "Realized") and agriculture and landcover to two of ARIES' domain ontologies, which among other content contain agricultural concepts (aligned, to the extent possible, with FAO's AGROVOC vocabulary) and a basic ontology for land cover types, respectively.

These definitions establish both the similarities and differences between the two definitions of the pollination ES, namely the distinction between "Potential" (GLOBIO-ES) and "Realized" (InVEST) and the broader definition of lands receiving pollination in InVEST ("Cropland" is a child concept of "AgriculturalVegetation"). Further work is needed to develop such semantics across a wider range of ecosystem services and achieve consensus on their use.

3.5. Applying semantics to quantitative ecosystem service assessments

Greater interoperability of ES models increases the flexibility of an interoperable system to choose the best model for the question being asked, rather than applying a single model to all problems. Given the well-known axiom that "all models are wrong, but some are useful" (Box, 1976), the ability to select the most appropriate model, rather than to rely solely on the most familiar model, as modelers often do (Melsen, 2022, Puy and Saltelli, 2023), is highly valuable. The ability to readily substitute alternative models for the same question aligns well with a *tiered ES modeling* approach, where more complex models can readily replace simpler ones when data exist and it is appropriate to do so (Kareiva et al., 2011, Martínez-López et al., 2019). A tiered ES modeling approach can be supported by recent work to build a living, crowd-sourced inventory of globally applicable ES models (Bulckaen et al., 2024). With appropriate AI assistance, the one-off or place-specific character of data and models can be turned from a limitation into an advantage, as AI can transparently substitute between ad-hoc and more generalized solutions when appropriate.

Drawing on a community-contributed body of knowledge offers far more flexibility than an individual ES modeler could ever achieve. Consider, for example, the case of soil erosion control modeling, for which ES modelers often apply variants of the Revised Universal Soil Loss Equation (RUSLE) model, despite its well-known limitations. A modeler tasked with assessing the impacts of land management programs on soil erosion might have relevant local datasets representing elevation, land cover, or soils, as well as information on agricultural practices. When local data are lacking, a modeler typically draws on more generalized (e.g., continental or global-scale) data. However, past research has described cases where alternative parameterizations and models are most appropriate (Benavidez et al., 2018; Table 1). If alternative approaches are available in an interoperable ES modeling system, a modeler could automatically reuse these, when appropriate to their region of interest. Additionally, a modeler might have knowledge of erosion processes of interest in their region that are poorly represented by RUSLE (e.g., erosion caused by wind, landslides, or streamflow, which causes streambank erosion). If a modeler knowledgeable of wind erosion modeling makes their model interoperable with other ES data

[7] While full consensus on such definitions may be desirable, harmonized typologies (e.g., to IUCN's Global Ecosystem Typology, Keith et al., 2022) and crosswalks can be challenging to develop, and a single universal classification may not meet all user needs. However, explicitly noting the typology used and appropriate reuse constraints would allow clearer explanation of model reuse criteria (e.g., use of "model X is appropriate in Dinerstein et al., 2017 Deserts and xeric shrubland biomes" or "dataset Y is appropriately applied in Sayre et al., 2020 Tropical moist world climate regions").

[8] These papers use a definition of ontology – the study of our understanding of reality – that is distinct but related to the definition used in this paper. In the former sense, pluralistic ontologies enable the coexistence of, for example, Western materialist and indigenous worldviews. This enables more diverse conceptualizations of complex, reciprocal human-nature relationships including instrumental, intrinsic, and relational values. In the latter sense, pluralistic ontologies undermine interoperability by applying, for instance, incompatible metadata keywords that compromise the ability of people or machines to reliably reuse data or models.

Table 1
Illustrative approach to achieving interoperability of multiple sediment regulation models using semantics. EU: European Union; NDVI: Normalized Difference Vegetation Index; RUSLE: Revised Universal Soil Loss Equation; RWEQ: Revised Wind Erosion Equation.

Erosion process/ Model	Usage considerations (human-readable)	Usage considerations (human & machine readable)*	References
Rill & sheet erosion/ RUSLE	Global equations & lookup tables for component RUSLE factors	Default approach when other below conditions are not met	Benavidez et al., 2018**
Rill & sheet erosion/ RUSLE	For RUSLE C factor, NDVI-based (C_{rA}) method most appropriate in tropical regions (evidence from Brazilian Cerrado)	Apply when modeling in an earth:Tropical earth:Region	Almagro et al., 2019
Rill & sheet erosion/ RUSLE	For RUSLE C factor, EU agricultural statistics used to estimate C factor in arable lands; % vegetation cover used in calculation for non-arable lands	Apply when modeling in the geography:European earth: Region or elsewhere that agricultural statistical data are available	Panagos et al., 2015
Streambank erosion/ Multiple approaches	Apply in regions where streambank erosion is known to be an important contributor of sediment	Apply when modeling in a user-specified hydrology: Waterway in geomorphic disequilibrium	Wilkinson et al., 2014
Landslide erosion/ Multiple approaches	Apply in mountain regions where landslides are known to be important contributors of sediment	Apply when modeling in an earth:Mountain earth:Region when geography:Slope > 18 %***	Alewell et al., 2008, Dow et al., 2024
Wind erosion/RWEQ	Apply in regions where wind erosion is known to be significant (e.g., Gholami et al., 2024)	Apply when modeling in an earth:Arid earth: KoppenGeigerClimateZone	Borrelli et al., 2017

*Examples here illustrate how stylized semantics referencing certain geographical settings can enable model customization, by applying those customizations when a model workflow is executed under those conditions.
**Benavidez et al. (2018) also list other regional and scale-specific adaptations of the five RUSLE factors, which could be coded for machine reuse similarly to the example from Almagro et al., 2019.
***The original USLE model specified that at slopes greater than this threshold, uncertainty would increase, implying the value of using alternative methods to quantify erosion from landslides.

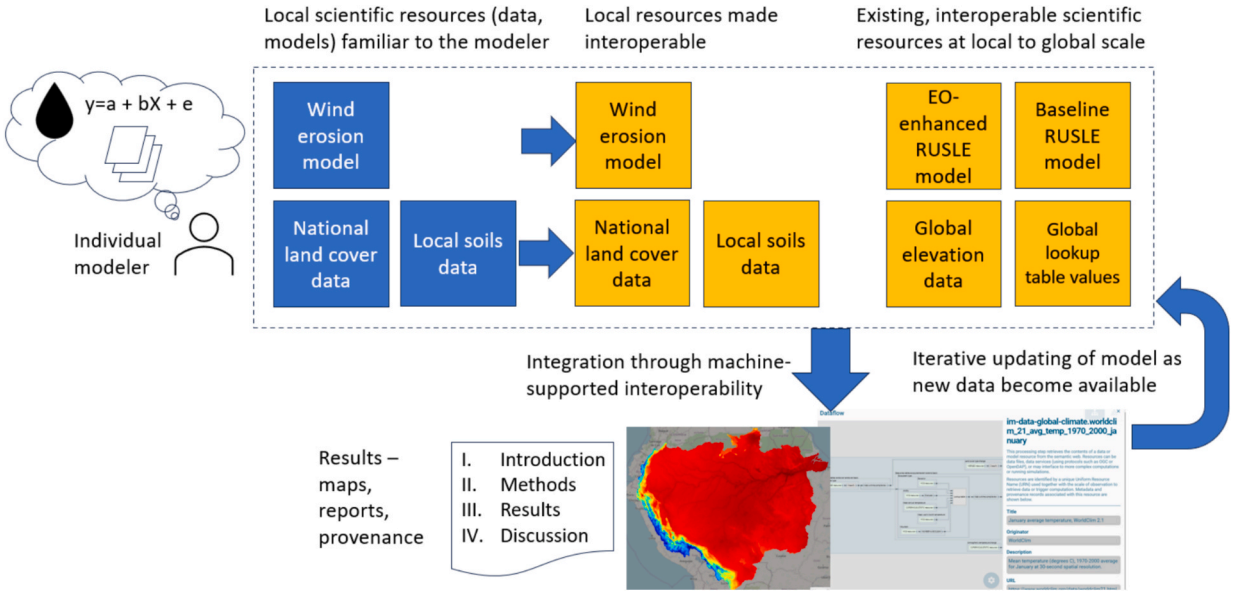

Fig. 2. An individual modeler, or even a small modeling team, will never have access to the comprehensive body of scientific knowledge relevant to their modeling problem. With access to interoperable scientific knowledge and the means to integrate it, a modeler can complete scientific tasks more rapidly, comprehensively, and reproducibly. Local scientific resources can also be contributed to a global knowledge commons (top two blue arrows and Fig. 3). EO: Earth observation; RUSLE: Revised Universal Soil Loss Equation.

and models, the wind erosion model could similarly be automatically reused when appropriate. Machine reasoning can then automatically assemble and execute the workflow most appropriate to the modeler's question. Benefiting from global datasets, multiple compatible modeling approaches, and local expertise, the modeler produces a state-of-the-art ES assessment (Fig. 2). This coupled workflow can then be re-run when updated or improved data or models become available, keeping the assessment current and relevant. By making their own work interoperable, modelers also improve others' work by providing knowledge that others can seamlessly reuse.

4. International ecosystem service initiatives and interoperability

Three major international initiatives – IPBES, SEEA, and GEO BON – share common aspirations for ES monitoring and accounting, but face challenges in integrating large bodies of knowledge at local to global scales. Below, we review the state of these initiatives with regard to interoperability.

4.1. IPBES

IPBES has five primary objectives – assessing knowledge, supporting policy, building capacity, strengthening knowledge foundations, and communication and engagement. IPBES' assessments, built around knowledge synthesis, are one of its most critical functions. Such assessments aspire toward achievement of both the FAIR Principles (Kim et al., 2023), and CARE Principles for Indigenous Data Governance (Collective benefit, Authority to control, Responsibility, Ethics; Carroll et al., 2020). Progress toward these objectives has been made, for example, in making

reporting of knowledge gaps, trends, and the status of nature from diverse knowledge systems more findable and accessible and in wider use of open and cloud-optimized file formats. An IPBES Ontology has been developed and used to support consistent reporting in literature reviews that underlie IPBES assessments (Dadvar and Niamir, 2024).

Interoperability would be an integral part of the ongoing IPBES monitoring assessment (IPBES, 2022b), which aims, among other goals, to support national and international efforts to monitor progress towards the goals and targets of the Kunming-Montreal Global Biodiversity Framework (CBD, 2022a). IPBES' second global assessment is scheduled to begin in 2026 and complete by 2030. IPBES aspires to deliver results of this assessment in a fully FAIR manner (Dadvar et al., 2024a, b, c), from key messages in the summary for policymakers to supporting subchapters and their underlying resources and references. Much work remains to achieve this, ranging from pairing containerized models with machine-actionable data to more widespread and consistent use of rigorous semantics to describe IPBES data, knowledge, and scenarios. Given its mandate to assess knowledge, there is also potential to use the FAIR Principles to improve the speed, transparency, and quality of IPBES' knowledge delivery to stakeholders during capacity building and regional outreach activities.

U.N. deliberative processes, which require consensus from all parties, have thus far yielded a slow uptake of the FAIR and CARE Principles. One reason for this is the unequal level of resources that countries can dedicate to IPBES and other Multilateral Environmental Agreements; those lacking resources also lack capacity to support implementation of new technical requirements like FAIR. This suggests the need for further attention to regional capacity building on interoperability, demonstration of the value it adds, and development of tools to facilitate its achievement.

4.2. SEEA EA

As an international standard for environmental-economic statistics, the SEEA by design involves formalization of definitions and methods that underlie consistent measurement and reporting on natural resources (SEEA Central Framework), ecosystems and ES (SEEA EA), and their connection to economic statistics. Creation and periodic updates to such standards follow an agreed development process that ultimately results in their adoption as standards by the U.N. Statistical Commission, which is comprised of national statistical offices from around the world (Edens et al., 2022). The U.N. Statistical Commission has guided the evolution of the System of National Accounts since the late 1940 s and the SEEA since the early 1990 s. Both systems require development of agreed concepts, definitions, measurement principles, and classifications, though their underlying definitions typically adhere to controlled vocabularies rather than ontologies. Given the inherent need for standardization that underlies national statistics, SEEA EA's definitions could be used to further formalize ES-related concepts into ontologies. The Statistical Data and Metadata eXchange (SDMX, 2024) is a set of standards, guidelines, and tools begun in 2001 to facilitate semantic interoperability of statistical data; its interoperability with SEEA EA data will support integration of ES with national economic accounts.

Starting early in its development, SEEA EA faced the challenge of quantifying ecosystems and their services. This required pairing the expertise of the statistical and ES modeling communities, and efforts to standardize ES definitions (e.g., U.N., 2021) and measurement approaches. National statistical offices play a critical role in producing SEEA accounts, but lack familiarity with geospatial data and interdisciplinary ES modeling. A typical solution to this problem is for national statistical offices to partner with national mapping, environmental, and natural resource agencies and academia to produce SEEA EA accounts, but such collaborations require time and effort to mature. The challenge of jumpstarting the process of SEEA EA accounts production led to a partnership between the U.N. Statistics Division and the ARIES Project to develop ARIES for SEEA, a semantic interoperability-focused approach to compiling ecosystem accounts (see Box 3).

Box 3
ARIES for SEEA and ARIES-4-PEOPLE: An interoperability-first approach to ecosystem services.

The ARIES Project (Villa et al., 2014) and its underlying open-source k.LAB software platform have been designed from its inception in 2007 to support semantic interoperability (Integrated Modelling Partnership, 2021). k.LAB combines: (1) machine-actionable data and models, (2) semantics to describe interdisciplinary scientific data and models supporting machine reasoning through ontologies (Villa and Adamo, 2024), which can (3) describe appropriate conditions under which to reuse data and models, enabling (4) a machine reasoning algorithm to select, assemble, and report results and provenance for scientific workflows.

Among other strategies, ARIES uses Open Geospatial Consortium Web Services to support machine actionability for data (see also Lacayo et al., 2021), as well as modern cloud-optimized technologies, like cloud-optimized GeoTIFFs indexed in Spatiotemporal Asset Catalogs (STAC, 2024). These strategies enable machines to request a specific dataset for a user-specified region and resolution; k.LAB automatically conducts needed geospatial operations (e.g., reprojection and resampling), unit conversion, and integration with other data and models.

Data and models in ARIES are semantically annotated in version-controlled projects. This approach balances privacy with transparency through a lifecycle designed to validate projects' content, enabling data and models to remain private or shared for public use as appropriate (Integrated Modelling Partnership, 2021). By design, k.LAB supports integration of a range of data and model types, from deterministic to probabilistic and machine learning models.

Given SEEA EA's need to assemble diverse data and models, a partnership between the ARIES Project and the U.N. Statistics Division created a web-based application, ARIES for SEEA (U.N., 2022), to facilitate SEEA EA's global implementation, and published a strategy document to promote interoperability of SEEA data and models (U.N. et al., 2023). The partnership maintains and extends the application and provides training and support to facilitate customization of SEEA accounts through contribution of interoperable data and models by the research and statistical communities (U.N., 2024). Web applications like ARIES for SEEA enable relatively rapid and user-friendly access to interoperable data and models by a range of stakeholders.

More recently, the European Space Agency-funded PEOPLE-EA Project has supported creation of computational infrastructure linking ARIES and its k.LAB client API (k.LAB, 2024) with the INCA tool (Buchhorn et al., 2022; see section 3.2) and openEO computational platform (ESA, 2024). This project improves the interoperability of the ARIES and INCA modeling components and their linkage to Earth observation data and SEEA EA data and models. Along with pilot testing the approach in five European countries, this project adds newly interoperable data and models for forest ecosystem condition (Maes et al. 2023) and soil erosion control (La Notte et al. 2021), enabling their automated assembly and reuse by ARIES in appropriate contexts when compiling SEEA EA accounts. This new system-of-systems environment enables the integration of available Python models with time-series Earth observation products through OpenEO.

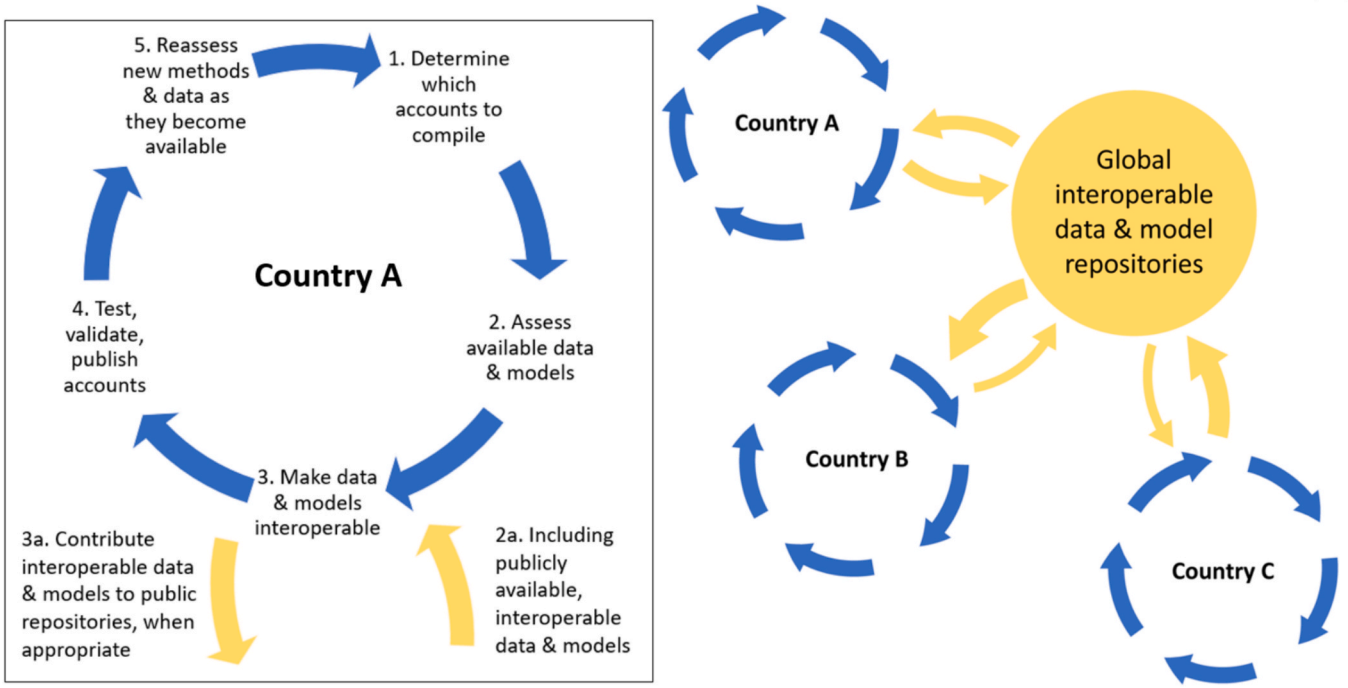

Fig. 3. A global knowledge commons to support implementation of the System of Environmental-Economic Accounting – Ecosystem Accounting (SEEA EA). Processes for an individual country are on the left. Countries will likely vary in their use of and contributions to a global knowledge commons (reflected by yellow arrows of varying width, right side of the figure). For further details, see U.N. et al. (2023). Concrete examples of contributions to an interoperable global knowledge base for SEEA include EU data and models for forest condition and soil erosion control accounts (see Box 3).

4.3. GEO BON

GEO BON works to develop biodiversity monitoring standards, synthesize global biodiversity knowledge, and guide decision making and policy (Scholes et al., 2012). Interoperability is required to support consistent measurement of biodiversity and ES and thus has been a core focus from GEO BON's inception. Essential Biodiversity Variables (EBVs) were developed to standardize data collection and track biodiversity change across scales and locations with substantial community engagement put into their semantics and interoperability (Kissling et al., 2015, Hardisty et al., 2019).[9]

More recently, "Essential Ecosystem Service Variables" (EESVs, Balvanera et al.., 2022) seek to extend the EBV concept to ES, but their development remains in its early stages (Schwantes et al., 2024) and little effort has been placed on their semantic underpinnings. Further work is needed to conceptualize and operationalize EESVs and their relationship to EBVs, as well as Essential Ocean and Climate Variables, supporting their interoperability (Mazzetti et al., 2022). The ESOnto ontology (Ayuningsih, 2019, Drakou et al., 2019) was designed to formalize relationships between ES concepts, to create a standardized path for information flow across ES classification systems, and underpinning ecosystem attributes, by linking to ENVO. The ESMO ontology, by contrast, focuses on monitoring ES, emphasizing the diverse biophysical and socioeconomic aspects of ES and data needed to do so (Affinito et al., 2024).

GEO BON also proposes the development of a cloud-based Global Biodiversity Observation System (GBiOS) patterned on the existing climate monitoring system, to integrate billions of observations into coherent predictive models (Gonzalez et al., 2023b, WMO, 2024). The GBiOS would be built upon EBVs and EESVs, enabling detection and attribution of biodiversity and ES change (Gonzalez et al., 2023a, b). Adherence to the FAIR and CARE Principles, and particularly interoperability, is critical for GBiOS. To support data analysis for GBiOS, GEO BON has developed "BON in a Box" (GEO GEO BON, 2024c), a user-directed (i.e., non-automated) tool to streamline EBV production using adaptable scripts and pipelines (Griffith et al., 2024). BON in a Box is programming language-agnostic and includes file format conversion scripts to support interoperability in its analysis pipeline. To date, it has not integrated formal ontologies or vocabularies. However, that would be a necessary and natural next step once the needed semantic resources are available. BON in a Box could also be adapted to produce EESVs. In parallel to GBiOS, GEO BON collaborators are developing an ES Observation Network for consistently monitoring ES. To become reality, such a system must develop operational EESVs with strong semantic underpinnings, and would benefit from integration with BON in a Box and ARIES.

4.4. International ecosystem services initiatives: Summary

While IPBES, SEEA EA, and GEO BON have important differences in their objectives, stakeholders, and capacity, they share two critical similarities – their (1) goal of monitoring and accounting for changes in ES over time and (2) need to integrate a complex and highly dispersed body of scientific knowledge at subnational through global scales. Achieving these goals – particularly the ability to produce scientifically robust, low-latency data – will be require a greater focus on interoperability by the initiatives themselves and the ES research community (Vári et al., 2024). The semantics, data, models, and scenarios supporting interoperability would also need to include closely related topics such as ecosystem extent and condition and integration with economic data (needed for SEEA EA), biodiversity (needed for GEO BON), and other nature-related themes (COP28, 2023).

[9] Specifically, the "Bari Manifesto" calls for the use of (1) data management plans, (2) common data structures, (3) metadata using community-accepted standards, (4) data quality control, (5) standardized APIs, (6) standard, reproducible workflows, (7) human and machine-readable provenance, (8) development and use of standard ontologies, (9) preservation in repositories using persistent identifiers, and (10) adherence to the FAIR principles (Hardisty et al., 2019).

Table 2
Problems and potential solutions an ecosystem services interoperability community of practice could address. ESP: Ecosystem Services Partnership, GEO BON: Group on Earth Observations-Biodiversity Observation Network, IPBES: Intergovernmental Science-Policy Panel on Biodiversity and Ecosystem Services, PECS: Programme on Ecosystem Change and Society, SEEA: System of Environmental-Economic Accounting, TNFD: Taskforce on Nature-related Financial Disclosures.

Challenge	Potential solutions
1. Community involvement	• Target key initiatives & organizations for involvement (e.g., Capitals Coalition, ESP, GEO BON, IPBES, PECS, SEEA, TNFD, key journal editorial boards) • Keep membership open to other interested parties • Ensure disciplinary diversity, strive to maximize participation from Global South
2. Clear goals	• Consider semantic interoperability as a key motivator • Provide descriptors for data & models underlying quantitative ES assessments & defining ES indicators or metrics relevant to ES monitoring • Consider how to address legitimate divergent worldviews in ES • If multiple types of semantic resources are deemed desirable, clarify their purposes
3. Limited scope	• Above scope excludes, for instance, qualitative research and indigenous knowledge for which imposition of a singular worldview is undesirable
4. Simple, intuitive structure	• Transparently discuss & debate pros & cons of major architectural choices • As starting point, strongly consider consensus described in section 3.1 (Leadbetter and Vodden, 2016, Stoica and Peckham, 2019, Maganga et al., 2021, Villa and Adamo, 2024) • Keep semantics parsimonious
5. Continuous evolution	• Acknowledge that semantics for ES are never "complete" but evolve to meet growth & change in the science
6. Active curation	• Long-term curation & dedicated process for updates • Commitment to & staffing of the effort as a public good for the ES community
7. Early use among demonstration projects	• Maximize ontology reuse by codeveloping semantics with users • Ensure usability through intentionally selected, collaborative pilot projects

Widespread use of interoperable data and models could transform these global initiatives, as national data producers, academics, and others could both provide data to, and draw data from, a global knowledge commons (Balbi et al., 2022). In the case of SEEA EA, national statistical offices and their partners tasked with developing ecosystem accounts could readily draw from federated, interoperable repositories, blend those data and models with their own national data and models, and, where appropriate, contribute their data and models to further enrich the global commons (Fig. 3). Academics and other researchers could also draw from, and contribute to, the same commons, maximizing the impact of their science. GEO BON envisions a similar process through BON in a Box and GBiOS, which would ideally be interoperable with the approach being advanced for SEEA EA (U.N., 2024).

SEEA and GEO BON also play key roles in supporting the implementation of monitoring for the Global Biodiversity Framework, e.g., Goals A and B and Targets 6, 11, and 21 (CBD, 2022b). Some components of the Kunming-Montreal Global Biodiversity Framework draw directly from SEEA EA, while others go beyond it, for instance by incorporating worldviews from different disciplines to identify trends in social-ecological systems and ES. Improved alignment with SEEA-based headline indicators (CBD, 2022b) and semantics from ARIES would thus be beneficial.

5. Next steps toward interoperability for ecosystem services

5.1. An interoperability community of practice for ecosystem services

Widely applied, community-endorsed semantic standards are needed to advance interoperability for ES, yet the semantic resources described in section 3.1 have important gaps and have not yet been widely adopted. Given this need, we believe a next critical step lies in the creation of a community of practice supporting interoperability across the ES community. Past efforts to engage the ES community, for instance, regarding data standards (Crossman et al., 2013, Drakou et al., 2015), have met limited participation, likely due to their perception as "too technical." Yet, improved interoperability is critical to address the knowledge fragmentation challenge that limits widespread ES and nature monitoring and reporting (i.e., TNFD, 2024). Despite the size of the challenge, it is notable that approaches needed to achieve interoperability can provide critical benefits to the ES community when applied consistently across different modeling approaches and platforms.

Returning to the notably successful example in genomics, such an effort could draw inspiration from that community's success criteria for semantics – "community involvement; clear goals; limited scope; simple, intuitive structure; continuous evolution; active curation; and early use" (Bada et al., 2004). Such an effort would ideally engage a diverse cross-section of the ES community, focus on the semantic interoperability challenge for quantitative ES assessments, make transparent and well-justified architectural choices, and strive for early use and continual evolution (Table 2). These criteria share overlap with the knowledge co-production literature, which suggests the importance of context-based, pluralistic, goal-oriented and interactive co-production processes (Norström et al. 2020). Finally, the experience of the Open Biological and Biomedical Ontologies (OBO) Foundry (Jackson et al., 2021) also offers valuable lessons.

Following from consensus on goals and key architectural choices, the key challenge will be establishment and consistent use of clear, meaningful concepts, as imprecisely defined or improperly applied semantics would lead to substandard results in an interoperable system (the well-known "garbage in-garbage-out" principle). Transparent provenance and an active user community are some of the best defenses against this. A community of practice would also contribute to ongoing awareness-raising on the importance of interoperability. Additionally, it could promote the "technical solutions" to interoperability that currently exist (i.e., using appropriate licensing, file formats, and APIs, section 2), yet are inconsistently used, and strive to make them easier to apply, for example, in organizations where technical expertise and resources are limited.

Power dynamics inevitably arise during standardization efforts (Steger et al. 2018), so representative participation of diverse groups, skillful facilitation, transparent processes, and careful scoping of effort are needed to ensure that standardization, e.g., for quantitative ES assessments, does not drown out other important forms of knowledge. Inherent challenges exist to readily addressing these power dynamics. First, knowledge engineering is a highly specialized field typically conducted in English, making expertise highly concentrated, with high real or perceived barriers to entry. Second, semantics carry a great deal of inertia: they are slow to develop, requiring substantial time investment by partners; simultaneously, the few individuals and groups already involved in semantics for ES have substantial incentive to carry their own work forward, posing challenges for achieving consensus. A useful starting point would be to clarify the purposes of existing semantic resources and transparently discuss and debate advantages and disadvantages of major architectural choices (e.g., which core/upper-level ontologies to use). This inertia problem is balanced against the urgency of scaling up national and global ES monitoring efforts (section 4), making efficient reuse of existing semantic and software resources valuable, as starting from scratch would be costly.

Finally, we note that the FAIR Principles are not a panacea for all

scientific data management challenges. Notably, the CARE Principles for indigenous data governance are increasingly important as indigenous and western scientific knowledge become more widely used in a complementary manner. The TRUST Principles (Transparency, Responsibility, User focus, Sustainability, Technology; Lin et al., 2020) provide guidance on the management of scientific repositories to support the FAIR Principles. Collective implementation of FAIR, CARE, and TRUST (O'Brien et al., 2024) provides a foundation for equitable open science. Similarly, effective data security measures and computational efficiency are important criteria for research software design that ES software developers must consider alongside the FAIR Principles (Lamprecht et al., 2020).

5.2. Transformative cultural changes supporting interoperability

Given the centrality of people to the challenge of interoperability (Ramage and Slotin, 2021), cultural changes can support its implementation in the ES field, beyond an interoperability community of practice. Cultural changes extend from individuals and research groups to structural changes in organizations.

For individuals, shifting mindsets around data sharing and interoperability are important. In past decades, scientists produced and managed their own data, giving limited thought to their reusability. This is changing through generational turnover and continued diffusion of open science principles (Campbell et al., 2019, Borycz et al., 2023). The potential for misuse is a frequently noted barrier to scientists' sharing of data (Perrier et al., 2020), and further work is needed to build effective guardrails around ES knowledge reuse. Interoperability will also benefit from individuals' efforts at community building that bridge various divides – by geography, disciplines, and research groups. These barriers exist for various reasons, including diverse training and backgrounds, multiple valid perspectives from which to understand ES, and academic incentives rewarding individualistic activities (Tiokhin et al., 2023). While there is no ready solution for breaking down these barriers, recognizing and uplifting our shared goals – and urgency to achieve robust ES monitoring as a global moonshot for our community – may be a useful starting point in overcoming it.

Additionally, structural support for interoperability within institutions is vital. Through their convening power, organizations can facilitate development and promotion of best practices, incentives, and other enabling conditions under which interoperability can progress.

International initiatives recognize the importance of interoperability, but devote varying levels of effort toward it (section 4, e.g., IPBES, 2022a, U.N. et al., 2023, GEO GEO BON, 2024d). Additionally, Ecosystem Services Partnership Thematic Working Groups 4 and 5 envision development of guidelines and standards for improved ES assessment (ESP, 2024). The World Bank faces similar challenges in its efforts to more comprehensively treat ES and natural capital in its Changing Wealth of Nations report (Bagstad et al., 2018). These groups and others can work individually and together to create and implement a shared vision for interoperability in ES.

Institutions, including funders, can create incentives rewarding collaboration over competition and develop collaborative networks of scientists. Science synthesis centers could play this role, as they have previously supported model integration (e.g., Iwanaga et al., 2021) and semantics (Leinfelder et al., 2011). Organizations will also likely play a role in the governance needed to support community-driven interoperability for ES (Chen et al., 2020, U.N. et al., 2023).

Funders and research institutions can advance interoperability by providing adequate funding for data management. They can also support career advancement through reward structures that move beyond a "publish or perish" mindset demanding ever-greater volume and speed

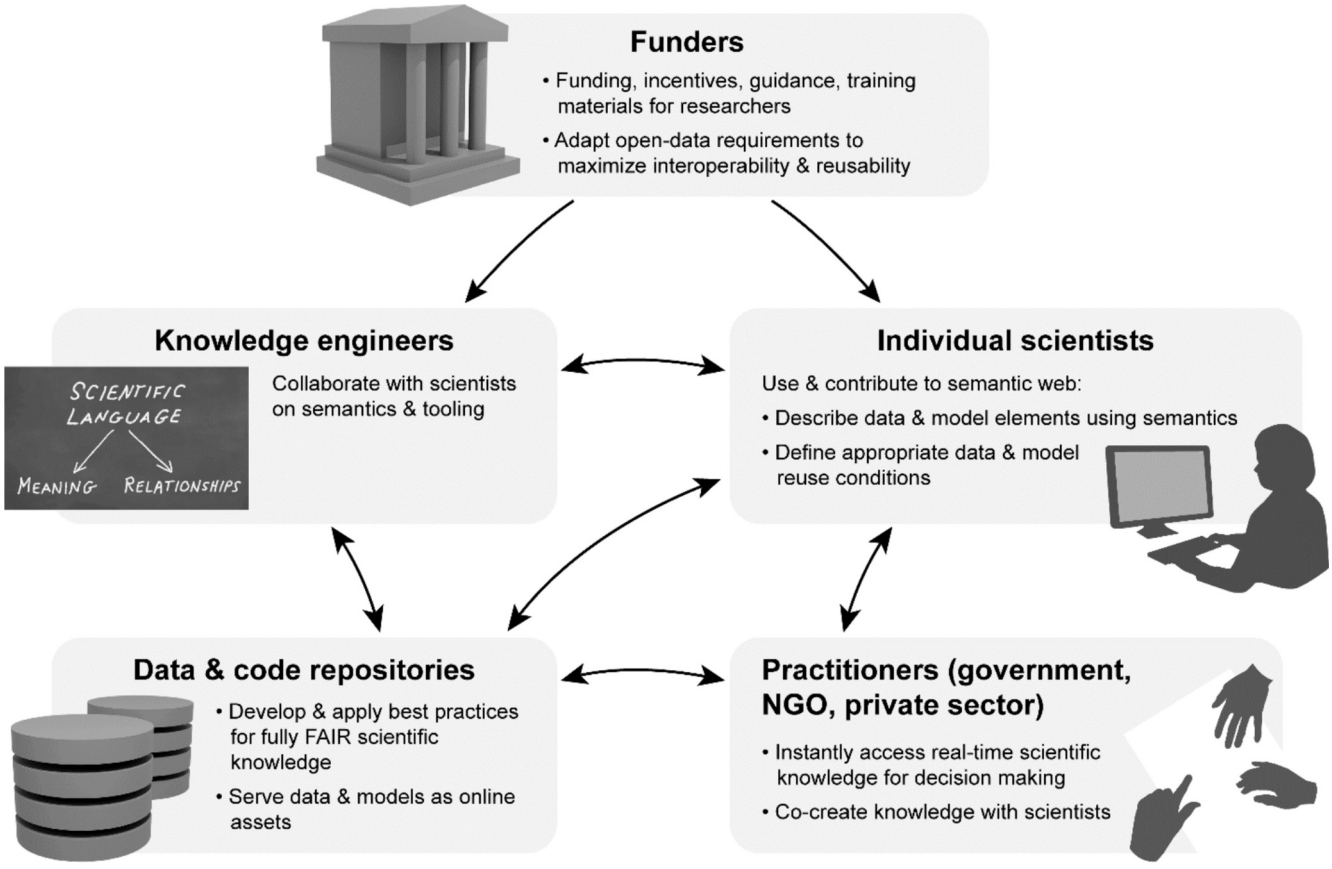

Fig. 4. Roles in the transition to interoperable science. FAIR: Findable, Accessible, Interoperable, Reusable; NGO: non-governmental organization. Adapted from Balbi et al., 2022, reproduced under CC BY 4.0.

of scientific publications, toward structures that reward the time and effort spent to make widely used, FAIR scientific products. Data and code repositories also play a central role in implementation of the FAIR Principles (e.g., DataONE, 2024, Tykhonov, 2024), and scientific journals can do so as well (Kitchener, 2022, INCF, 2023).

Finally, organizations can help ensure that methods supporting interoperability for ES are available and applied in the Global South, supporting capacity building, equitable access to, and application of knowledge about ES to decision making. Doing so is critical to ensure that scientific knowledge contained in an interoperable knowledge base is globally representative (Schirpke et al., 2023).

5.3. The interoperable ecosystem service assessment of the future

ES assessments built upon FAIR data, models, and software are needed to support ES and ES-adjacent monitoring and accounting frameworks (section 4; Vaz et al., 2021; Balvanera et al.., 2022; Gonzalez et al., 2023a). In this future, as new input data are generated, ES models will be able to be re-run to provide continuously updated datasets and time series; as such data become increasingly timely, ES monitoring will move closer and closer to real-time. When novel data, models, and model parameterizations become available, new results can be benchmarked against previous data for regions of interest to maintain consistent time series. Ongoing work will continue to develop localized knowledge and more accurately represent heterogeneous local-scale processes that underpin ES. This local-scale knowledge can then be integrated into improved regional, national, and global assessments, as appropriate (Chaplin-Kramer et al., 2024).

Interoperable ES knowledge carries obvious benefits for widening access to information – "democratizing" the science and its application (Carmen et al., 2018), particularly in capacity-limited environments including the Global South. Most ES modelers are familiar with the process of spending weeks to months searching for, downloading, reformatting, and cleaning data. This puts two critical constituencies at a disadvantage – (1) younger, less experienced and well-connected researchers with less knowledge of data resources spread across many repositories and having smaller social networks to facilitate data requests (Gregory et al., 2019) and (2) decision makers who need more rapid answers than time-consuming modeling processes can provide. By substituting individual modelers' *internal knowledge bases*, which vary widely based on experience, with a growing, community-driven, *machine-actionable knowledge base*, knowledge in the ES field can become additive and users' capabilities greatly enhanced. An interoperable system can also enable the use of a tiered ES modeling approach (Kareiva et al., 2011; Martínez-López et al., 2019; U.N., 2022).

This level of interoperability will require changes in how scientists, modelers, and data providers think about and manage their knowledge (Balbi et al., 2022, Fig. 4). Achieving interoperability requires work (Santoro et al., 2020), and platform developers must carefully consider how to lower barriers to entry for both end users and contributors of scientific knowledge, including early- to late-career scientists, data stewards, and managers of scientific repositories. Data and model developers will likely view further steps to make their products interoperable as burdensome unless substantial efforts are made to make these additional steps as efficient and rewarding as possible.

5.4. Conclusions

The recognition that standards are needed for ES data management and reporting is not new (Crossman et al., 2013, Drakou et al., 2015, Edens et al., 2022). We believe that today's ES modeling community faces the choice between a status quo of increasingly fragmented, non-FAIR data, models, and software, versus coalescing around shared community solutions to the interoperability and reusability problem. The adoption of such solutions could take many years, or be accelerated by the involvement of key organizations and individuals. As such, the interoperable ES assessment of the future (sections 3.5 and 5.3) need not necessarily be that of the far future. While any improvements in FAIR ES data, models, and software are valuable steps forward, incremental advances are not commensurate with the urgency of providing ES information to address pressing global challenges (Balbi et al., 2022).

FAIR knowledge could enable ES assessments to increasingly shift from human-driven to faster, more automated integration of interoperable data and models (Laniak et al., 2013, Belete et al., 2017). Platforms supporting interoperability can ideally blend both adaptability and power – for instance, providing substantial flexibility for very technical modelers and programmers, while hiding complexity that is unneeded by novice users, yet still providing provenance (Gries et al., 2018, Spiekermann et al., 2019) to maintain transparency in the modeling process (e.g., U.N., 2022). Done well, interoperable ES data, models, and software can support global monitoring for a range of high-visibility efforts requiring integration of diverse data. These include IPBES, SEEA, and GEO BON, but also the Sustainable Development Goals (Gonzalez Morales and Orrell, 2018, Revez et al., 2022) and Taskforce on Nature-related Financial Disclosures that is exploring creation of a "global nature-related public data facility" (TNFD, 2024), which would benefit from a focus on interoperability with other ES initiatives. Through appropriate reuse of tailored knowledge, credible and high-quality reporting on ES will also play a critical role in the sustainable digital transformation (CODES, 2024). At the same time, we recognize that real limits likely exist on the interoperability of certain types of ES data, e.g., those collected using participatory methods and drawing from indigenous knowledge.

Despite the size of this challenge, we see reason for optimism. Ten to fifteen years ago, graduate students were not routinely taught to code using collaborative tools, nor did scientists regularly use public data and code repositories. Interoperability and reusability for ES and science more broadly are natural next steps toward greater transparency and reproducibility. In an age of ever-expanding scientific knowledge, we agree with Hampton et al. (2013) that scientists who effectively share and reuse data will ultimately do the most valuable research, conducting more novel, timely, and broad syntheses that bring new perspectives to past datasets. Given the urgency of confronting global environmental challenges with actionable evidence (Balbi et al., 2022, COP28, 2023) and at a time when scientific knowledge is growing too quickly for individual scientists to keep up with (Borycz and Carroll, 2020), we believe the time is ripe to expand the level of engagement on interoperability for ES across our community.

CRediT authorship contribution statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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