Ecosystem Services 80 (2026) 101871

Contents lists available at ScienceDirect

Ecosystem Services

journal homepage: www.elsevier.com/locate/ecoser

Full Length Article

Artificial Intelligence for ecosystem services science: The AI4ESS framework from a community perspective

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ARTICLE INFO

Keywords:
Governance
Ecosystem Services (ES)
Decision Support
Interdisciplinary Collaboration
Environmental Data and Ethics

ABSTRACT

Ecosystem services (ES) research draws on heterogeneous biophysical, socio-economic, and valuation data that are often collected at different scales and structured using incompatible classifications. This paper presents a community-based synthesis of how Artificial Intelligence (AI) can be responsibly embedded in Ecosystem Services Science (ESS) through the AI4ESS framework, developed from two structured expert dialogues organized under the Ecosystem Services Partnership (ESP) network. Drawing on interdisciplinary insights from researchers, practitioners, and policymakers, the AI4ESS framework is defined as a four-dimensional conceptual structure integrating challenges, ethics, data and models, and opportunities to guide transparent and equitable AI adoption in ES research and in subsequent decision support. The AI4ESS framework extends approaches such as GeoAI and AIXES by integrating ethical, governance, and knowledge-inclusion principles alongside technical considerations. It identifies key priorities for advancing responsible AI in ESS: improving data transparency, promoting explainable and open models, establishing community-driven ethics guidelines, and fostering collaboration between domain and AI experts. This synthesis provides a conceptual foundation for integrating AI into ES valuation and decision support. By articulating actionable pathways, the framework contributes to the development of trustworthy, inclusive, and scalable AI applications that strengthen sustainability governance and evidence-based ecosystem management.

1. Introduction

Artificial intelligence (AI) is transforming many areas of science, including Ecosystem Services Science (ESS), yet important questions remain regarding its responsible use, ethical implications, and integration with the socio-ecological perspectives central to Ecosystem Service research (Goralski and Tan, 2020; Hák et al., 2016). AI refers to computational systems capable of performing tasks that typically require human intelligence. Machine Learning (ML) forms the foundation of many modern AI systems, with deep learning representing an important subset particularly suited to large-scale data processing and pattern recognition. Recent advances have also led to the development of Large Language Models (LLMs), which can analyse and generate text and are increasingly used for tasks such as literature synthesis, knowledge extraction, and decision support. When applied within sustainability-oriented research contexts, these capabilities offer new potential for environmental analysis, prediction, and decision-making (Goralski and Tan, 2020; Schirpke et al., 2023).

In ESS, these capabilities support applications such as large-scale classification of Earth observation data, automated extraction of information from scientific literature, policy documents, and other textual sources, and computer-vision approaches for biodiversity monitoring and ecosystem condition assessment (van der Plas et al., 2025). Foundational work has demonstrated the potential of machine learning to advance ecosystem services modelling and mapping (Willcock et al., 2018). Recent syntheses further confirm AI's expanding role in real-time monitoring and comprehensive ES assessment (Han et al., 2025).

However, the integration of AI in ESS remains limited and faces ethical, interpretability, and accessibility challenges (Galaz et al., 2021; Nti et al., 2022). In this context, environmental science increasingly

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https://doi.org/10.1016/j.ecoser.2026.101871
Received 28 October 2025; Received in revised form 16 May 2026; Accepted 16 May 2026
Available online 24 May 2026

relies on technological advances to monitor and assess human-nature interactions, with AI emerging as a powerful approach for analysing the complex socio-ecological datasets central to ESS (Schirpke et al., 2023). AI methods are well suited to large-scale data integration, pattern detection across heterogeneous biophysical and socio-economic systems, spatial and temporal extrapolation, and scenario exploration under alternative assumptions (Han et al., 2025; Nishant et al., 2020). By automating labor-intensive tasks such as image classification and document analysis, AI can reduce analytical costs, improve consistency when appropriately designed and validated, and accelerate evidence synthesis across diverse environmental and socio-economic data sources. Emerging platforms such as Planet Labs and FlintPRO illustrate the operational potential of AI-enabled monitoring and decision support (Chen et al., 2024; Yadav and Singh, 2023).

Despite these opportunities, the ESS community has not yet fully addressed many of the technical, ethical, and governance questions raised by the integration of AI. The incorporation of AI into ESS raises several challenges, including data biases, limited interpretability of complex machine-learning models (Rudin, 2019), and the difficulty of representing socially constructed ES values using purely data-driven approaches. AI is also often limited in addressing questions involving normative judgments, contested social values, and context-specific trade-offs-core dimensions of many ES assessments. Moreover, AI outputs may be incomplete or systematically biased (Vaghefi et al., 2023), and critical expertise gaps persist: environmental researchers often lack advanced AI training, while AI specialists may misinterpret ecological and social contexts (Zamfirescu-Pereira et al., 2023). Accordingly, domain experts remain essential to ensure interpretability, transparency, and ethical use. Co-developing AI tools with ESS experts is essential for maintaining trust and scientific rigor (Bibri et al., 2024). While recent studies have discussed GeoAI applications in environmental and ES contexts (Karpatne et al., 2017; Schirpke et al., 2023; Zhu et al., 2017), none have systematically integrated community perspectives into a framework that jointly addresses technical, ethical, and governance dimensions of AI adoption in ESS.

These challenges highlight the need for AI guidance developed in collaboration with the ESS community, motivating the expert dialogues conducted within the Ecosystem Services Partnership (ESP) network that form the empirical basis of this study. Participants in the ESP, a global network of researchers and practitioners focused on ES, highlighted during expert dialogue sessions the absence of shared ethical guidelines, uneven technical capacity across the ESS community, and concerns regarding transparency and data governance. These issues collectively motivated the development of the AI4ESS framework proposed in this study as a community-informed approach for guiding the responsible integration of AI in ESS.

ESS encompasses a broad range of research activities, including biophysical assessments, economic and non-monetary valuations, governance analyses, participatory approaches, and the study of cultural and relational values, spanning quantitative, qualitative, and mixed methods (IPBES, 2019). Against this backdrop, the need for co-producing AI tools is particularly pronounced in ESS due to several field-specific characteristics. ESS uniquely integrates biophysical modeling with socially constructed values, linking ecological processes to human well-being, policy priorities, and normative judgments (Costanza et al., 2017; Díaz et al., 2018). Outputs from ESS assessments frequently inform environmental planning, conservation investment, and regulatory decisions that affect diverse stakeholder groups and communities, including Indigenous and resource-dependent populations. In addition, ESS relies heavily on spatially explicit data and mapping-based representations, which can embed distributional assumptions and equity implications that are amplified when automated through AI (Schirpke et al., 2023). These characteristics distinguish ESS from many other scientific domains and heighten the ethical sensitivity of AI deployment, making collaborative co-design with domain experts, decision-makers, and local knowledge holders essential for effective AI deployment in ESS (Mienye et al., 2024; Willcock et al., 2018).

Against this background, this paper proposes the AI4ESS framework, a structured and community-informed approach for guiding the responsible integration of AI within ESS. Specifically, we seek to address three guiding questions: (i) what technical, ethical, and governance challenges currently constrain the use of AI in ES assessments; (ii) where AI methods can meaningfully support ESS research and decision-making, and where their limitations require complementary human judgment and participatory approaches; and (iii) how community perspectives can be systematically incorporated to guide the co-development of AI tools that are transparent, inclusive, and context-aware. By addressing these questions, the AI4ESS framework clarifies the role of AI in ESS and provides a shared reference point for researchers, practitioners, and policymakers.

2. Community-based exploration of AI in ecosystem Services science

The AI4ESS framework draws on two structured expert dialogue sessions conducted within the ESP community: the 5th ESP Europe Conference in Wageningen, The Netherlands, 2024, and the 11th ESP World Conference in Darwin, Australia, 2025. These sessions aimed to identify shared challenges, priorities, and opportunities in integrating AI into ESS.

The first session took place during the ESP Europe Conference in 2024 and brought together approximately 50 participants from diverse disciplinary backgrounds. Using a structured expert elicitation approach, participants engaged in breakout sessions to identify key challenges and opportunities associated with applying AI in ESS. Discussions were organized around predefined themes and followed a modified Delphi-style process to capture interdisciplinary perspectives. Notes from the breakout groups were thematically coded and consolidated into four overarching dimensions that structure the analysis presented in Section 3.

A short follow-up survey distributed to session participants further illustrated the diversity of interests within the emerging AI-ESS community. Respondents highlighted modelling approaches, data validation, and methodological development as key areas of interest (Fig. 1). The prominence of general terms and ethical considerations in these responses suggests that AI remains an emerging topic within the ESS community, with uneven familiarity across participants.

The results of the first workshop were further developed during a second session held at the 11th ESP World Conference in Darwin, Australia, 2025, which involved approximately 20 participants. Discussions were organized into four breakout groups addressing: (i) knowledge considerations, (ii) data and modelling issues, (iii) ethical and equity challenges, and (iv) opportunities for scaling AI applications in ESS. Participants emphasized that AI should support rather than replace expert reasoning and highlighted the importance of metadata documentation, data lineage, and ownership transparency to ensure model validation and trust. Ethical discussions focused on bias and representation, stressing that effective governance depends on clearly defining who can access, interpret, and correct biased information.

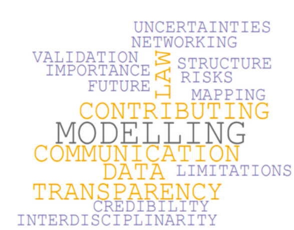

Fig. 1. Keywords derived from a survey of declared areas of interest and expertise among participants of the ESP session on AI and ES. Font size reflects the frequency of keyword occurrence.

Participants also emphasized the importance of extending AI benefits to diverse ecosystems and communities. Across both sessions, participants repeatedly highlighted the absence of shared ethical guidelines, uneven technical capacity within the ESS community, and the need for transparent data and modelling practices when applying AI.

Across both sessions, participants expressed strong support for establishing an AI–ESS working group within the ESP network to facilitate continued collaboration and knowledge exchange. Such a group could help develop community-driven standards, support responsible AI development, and strengthen the integration of AI approaches within ES research and practice. In response to these community-identified challenges, the AI4ESS framework is proposed as a structured approach to guide the responsible integration of AI in ESS (Fig. 2).

3. Integration of Artificial Intelligence in ecosystem Services

3.1. Challenges and considerations for Artificial Intelligence in ecosystem Services

The integration of AI into ES research is constrained by a set of specific and recurring challenges that shape where AI methods can and cannot meaningfully contribute. These challenges arise from the multi-scale nature of socio-ecological systems, the heterogeneity of ES indicators, and the presence of normative and value-laden dimensions that extend beyond purely biophysical representation (Egarter Vigl et al., 2021; Schirpke et al., 2021). AI methods, particularly when combined with remote sensing and other forms of spatial imagery, show strong potential for generating ES information across large spatial extents and long temporal horizons that are otherwise difficult or costly to assess (Karpatne et al., 2017; Schirpke et al., 2023). In contrast, AI approaches are far less effective in contexts where ES valuations are diverse, contested, or socially constructed, such as cultural services or distributional trade-offs, where interpretation and deliberation cannot be inferred from data patterns alone (Gao et al., 2024). In such cases, AI systems may support tasks such as synthesizing divergent viewpoints, translating complex scientific information into accessible language for diverse audiences, and enabling structured comparison of alternative perspectives in ES assessments. However, LLMs and related AI tools can reproduce biases present in their training data, particularly when certain languages, cultures, or worldviews remain underrepresented (Dentella et al., 2026; Gallegos et al., 2024).

Equally important is the relationship between AI systems and human expertise in ES research (Bibri et al., 2024; Chen et al., 2024). Current approaches increasingly frame AI as part of human-AI collaborative workflows, where models function as decision-support tools within human-in-the-loop analytical processes rather than as autonomous replacements for expert judgment (Villa et al., 2014). In such settings, AI can assist with tasks such as pattern detection, evidence synthesis, and scenario exploration, while researchers provide contextual interpretation, validation, and ethical oversight. At the same time, AI systems inherit biases and limitations present in their training data, which may underrepresent certain regions, languages, or knowledge systems. Recent efforts to broaden training datasets, including the integration of multilingual literature, Indigenous knowledge sources, and non-Western environmental knowledge, highlight the importance of diverse and well-governed data foundations for responsible AI-supported ES research (Galaz et al., 2021; Nti et al., 2022; Zhu et al., 2023).

3.2. Data and model related challenges

Data-related challenges in AI-based ES models are multifaceted and extend beyond data volume to include transparency, geographic bias, and uncertainty in model outputs (Schirpke et al., 2023). Transparency can be improved through comprehensive metadata documentation that clearly describes data provenance, preprocessing steps, assumptions, and known limitations, thereby enhancing interpretability and user trust (Sarker, 2022). Well-documented metadata is particularly important in AI-based ES assessments, where complex data pipelines can otherwise

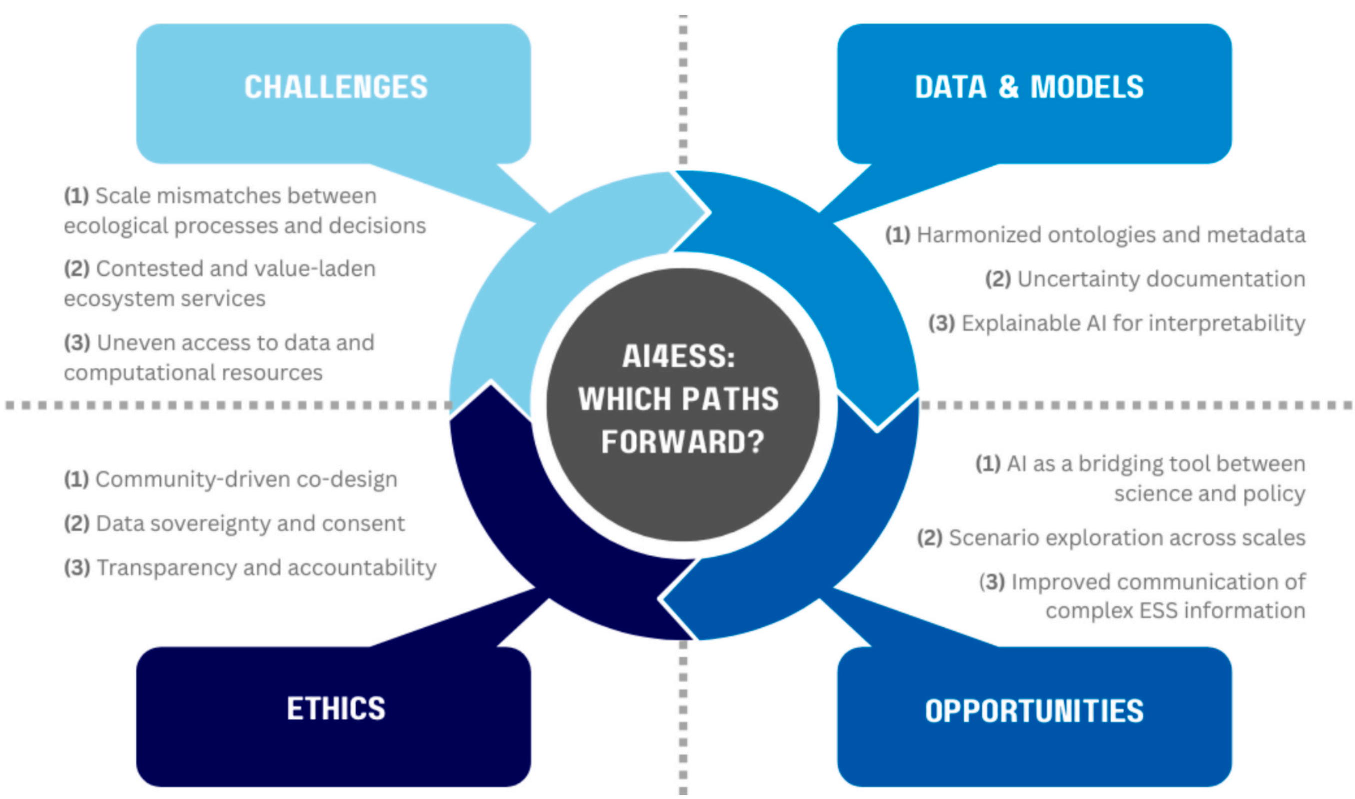

Fig. 2. The four-dimensional AI4ESS Integration Framework.

obscure the origins and meaning of model outputs.

Within the AI4ESS framework, data availability and bias are addressed through data harmonization as a practical process rather than a purely technical objective. Harmonization involves aligning ontologies and variable definitions across datasets to support interoperability while preserving region-specific ecological characteristics. This is especially relevant given that biodiversity and environmental datasets remain disproportionately concentrated in Europe and North America, resulting in substantial geographic bias and underrepresentation of many ecosystems (Valdez et al., 2024). Without explicit attention to these imbalances, AI-based ES models trained on such data may produce skewed or misleading results when applied in data-scarce regions (Nishant et al., 2020).

In practice, AI4ESS emphasizes combining standardized data structures with partnerships involving local researchers and institutions to contextualize, validate, and interpret AI-ready datasets, thereby reducing the risk of systematic bias. Beyond ecological datasets, the framework also highlights the importance of incorporating more diverse textual and knowledge sources, including multilingual scientific literature, regional policy documents, and locally grounded ecological knowledge, to reducing the linguistic and epistemic biases in AI-supported ES assessments.

Model design choices further influence trust and usability. When policymakers rely heavily on biophysical proxies to represent ES indicators, AI-based assessments may fail to capture ecosystems as coupled social-ecological systems, leading to skepticism and limited policy uptake (Gao et al., 2024). Integrating geospatially capable AI approaches with process-based ES models can help address this limitation by preserving spatial context and ecological mechanisms, thereby yielding more robust, location-aware assessments (Egarter Vigl et al., 2021). Bayesian modeling approaches can further support uncertainty representation, although defining acceptable uncertainty thresholds remains a key challenge in decision-oriented ES applications (Bagstad et al., 2014; Vigerstol and Aukema, 2011).

Explainable Artificial Intelligence (XAI) techniques provide a complementary mechanism to improve model transparency and interpretability. For example, in a machine-learning model predicting ES outcomes such as carbon sequestration or flood regulation from climatic, land-use, and remote sensing variables, feature attribution methods (e.g., SHAP values) can be used to explicitly identify which inputs drive model predictions across regions. Such analyses make it possible to detect whether outputs are dominated by data-rich proxy variables or reflect ecologically meaningful relationships, thereby supporting critical evaluation by domain experts and non-technical stakeholders (Minh et al., 2022; Mumuni and Mumuni, 2025). By revealing model behavior rather than treating AI outputs as black boxes, XAI supports informed interpretation and responsible use in ES decision-making contexts.

Despite the rapid growth in spatial data availability, particularly from Earth Observation missions, validation remains a persistent challenge due to limited availability of ground-based reference data and the high costs of data collection (Egarter Vigl et al., 2021). Data gaps and inconsistencies therefore continue to constrain AI-based ES models (Gao et al., 2024). AI4ESS addresses this tension by emphasizing fitness-for-purpose validation, in which the level of model complexity, uncertainty handling, and validation effort is matched to the intended decision context.

At the same time, accessibility concerns arise from the computational resources and technical expertise required to develop and apply AI-based ES models. Recent advances in lightweight AI models designed for mobile and low-resource environments suggest that some hardware-related barriers may gradually decrease. However, linguistic accessibility remains a major challenge, as many AI systems are still trained predominantly on English-language datasets. Ongoing efforts to expand AI training resources to include African and other underrepresented languages highlight the importance of multilingual AI development for equitable access to AI-supported ES research (Mienye et al., 2024). A recent review further highlights how machine learning and big data approaches can help address major knowledge and methodological gaps in ecosystem services research (Manley et al., 2022).

Promoting user-friendly, scalable tools and lowering computational barriers are thus essential for broad adoption and equitable use (Schirpke et al., 2023). While advanced algorithms can partially mitigate missing or inconsistent data, responsible application requires transparency about these limitations and their implications for ES assessment outcomes (Bagstad et al., 2014; Vigerstol and Aukema, 2011).

Underlying all these data and model related challenges, an additional, often underexamined dimension of responsible AI deployment concerns the environmental footprint of the digital infrastructure that underpins AI systems, particularly data centers (Schwartz et al., 2020; Strubell et al., 2020). While energy consumption and associated carbon emissions are frequently highlighted, data centers also have broader environmental and socio-economic impacts, including land-use change, water demand for cooling, and localized ecological disturbance (Mytton, 2021). These impacts are spatially uneven and can affect surrounding communities and ecosystems, raising questions of environmental justice and regional trade-offs (Bender et al., 2021). Given ESS's focus on coupled social-ecological systems, the ESS community is well positioned to contribute to integrated assessments of data center development, evaluating not only energy efficiency but also land-use, biodiversity, water, and socio-economic implications. Incorporating such assessments into AI governance discussions can help ensure that the expansion of AI infrastructure aligns with sustainability goals rather than undermining them.

3.3. Opportunities and the future of AI in ecosystem Services

AI offers transformative opportunities in ES research (Nishant et al., 2020; Schirpke et al., 2023). One of its most significant contributions is its role as a translation tool, bridging disciplinary silos, languages, and perspectives (Mohamed et al., 2024). Bringing together diverse perspectives is essential for addressing the cross-disciplinary challenges inherent to ESS. It also helps with larger goals such as protecting and restoring biodiversity, ensuring equitable and sustainable resource use, and advancing the Sustainable Development Goals (SDGs) (Goralski and Tan, 2020). AI can enhance the accessibility of scientific knowledge by translating complex data into digestible formats for policymakers and the public, using tools such as visual representations and augmented reality (Muccione et al., 2024; Zhu et al., 2023). In such contexts, AI systems, including LLMs, can support knowledge synthesis and communication across diverse stakeholders. However, when applied to value-laden questions, these systems may reproduce biases embedded in their training data, particularly where certain languages, cultures, or knowledge systems are underrepresented. Furthermore, their ability to verify the credibility of data and sources can support transparency and foster trust in decision-making processes (Bibri et al., 2024; Villa et al., 2014).

AI may also support ES valuation by synthesizing large volumes of economic studies, policy documents, and stakeholder inputs, enabling more systematic comparison of diverse valuation approaches and societal perspectives (Schirpke et al., 2023). For example, deep learning combined with benefit transfer has been successfully applied to value cultural ecosystem services (Lingua et al., 2022). However, such applications must account for potential biases embedded in training data and ensure that diverse cultural and knowledge systems are adequately represented.

Lessons from other disciplines that have adopted AI at scale, including healthcare, climate science, and data-intensive social sciences, show that realizing these opportunities requires embedding domain knowledge directly into AI development rather than relying on generic, data-driven models. In these fields, approaches such as theory-guided

ML, hybrid modeling, and domain-specific training datasets have been shown to improve interpretability, robustness, and trust in AI-supported decision-making (Karpatne et al., 2017; McGovern et al., 2022; Rudin, 2019). For ESS, this implies that future AI tools should be trained not only on large observational datasets but also on the best available community knowledge, including established conceptual frameworks, expert judgment, and locally grounded insights (McGovern et al., 2022). Such knowledge-informed AI development can help address persistent challenges related to bias, context sensitivity, and ethical use while enhancing the relevance of AI applications for ES assessment and governance.

Recent advances in AI further suggest that some of the contextual and accessibility barriers identified in ESS are increasingly tractable. In particular, a growing body of work on LLMs and multimodal AI focuses on training models with more diverse linguistic, cultural, and epistemic corpora. These efforts include multilingual scientific literature, regional policy documents, and emerging initiatives to incorporate Indigenous and non-Western knowledge sources. Together, they demonstrate improved performance across languages, regions, and knowledge contexts that have historically been underrepresented in data-intensive research (Lupaşcu et al., 2026; Nyandwi et al., 2025). Such approaches have been shown to support cross-lingual knowledge transfer, contextual interpretation, and engagement with non-English scientific and policy communities (Bender et al., 2021; Devlin et al., 2019; OpenAI, 2024). While these models do not resolve normative or value-based challenges inherent to ES assessment, they provide a feasible technical basis for reducing linguistic and contextual biases when combined with domain expertise and community-driven validation. As AI capabilities continue to evolve, their role in ESS is increasingly understood in terms of human-AI collaboration, where AI systems function as decision-support tools embedded within human-in-the-loop analytical workflows (Debnath et al., 2025; McGovern et al., 2022). In such settings, AI assists with data synthesis, pattern detection, and knowledge translation, while human experts provide contextual interpretation, ethical oversight, and validation of results. Ongoing efforts to expand AI training corpora, including the integration of non-Western scientific literature, Indigenous knowledge sources, and multilingual datasets, may further support more inclusive representations of diverse knowledge systems in AI-enabled ES research, provided that these efforts are accompanied by appropriate governance and community engagement (Ijatuyi et al., 2025).

3.4. *Ethical considerations and strategies to ensure that AI tools amplify, rather than overshadow, indigenous and local perspectives in decision-making processes*

The integration of ML and LLMs in ES presents both transformative opportunities and critical ethical challenges (Schirpke et al., 2023). A key consideration is the separation between AI models and the regulation of *meta*-AI data, which raises concerns about data privacy, transparency, and control (Nti et al., 2022). While these technologies can be cost-effective, their reliability hinges on clear guidelines for the underlying data and model validation. Many ML and LLMs systems operate as black boxes, obscuring the origin, quality, and biases of the data they process and how they are processed (Gao et al., 2024; Glessmer and Forsyth, 2025; Muccione et al., 2024). AI systems face several challenges, including (1) biased or non-representative training data, (2) flawed model training strategies and the risk of models learning misleading or inappropriate behaviors, and (3) societal concerns arising from the lack of consent in data use, the environmental impact of AI development, and the potential marginalization of researchers and initiatives, particularly in developing countries (Glessmer and Forsyth, 2025; McGovern et al., 2022).

There is an inherent risk that models may "give you what you want", reflecting user biases rather than objective truths, particularly in environmental contexts where scientific rigor is paramount (Zamfirescu-Pereira et al., 2023). This misplaces a heavy responsibility on researchers to use these technologies ethically, for example, employing sandbox environments (i.e., controlled testing settings) for testing and ensuring thorough, transparent validation before deployment, when it should be AI modelers and companies that take responsibility for co-developing these technologies ethically in the first place. Corresponding technological development guidelines must consider not only economic and computational costs but also environmental and social impacts, including the substantial energy demands of AI systems (Muccione et al., 2024). Higher-level rules on AI are needed to make sure that models are checked by local experts (e.g., in industry-university cooperations) who can put the results into ecological and cultural contexts (Bibri et al., 2024). Without careful oversight, there is a risk of perpetuating biases, reducing the reliability of AI-driven insights, and ultimately compromising the integrity of ecosystem management (Egarter Vigl et al., 2021; Glessmer and Forsyth, 2025). Despite these insecurities, however, there is a consensus that AI models should be used in future ES studies (Sun and Scanlon, 2019).

4. AI4ESS: Which Paths Forward?

Building on the preceding analysis, this section focuses on two practical priorities for advancing AI integration in ESS. Since ESS integrates biophysical processes, socio-economic valuation, governance considerations, and spatial decision-support, generic AI guidance is often insufficient for ESS applications. Accordingly, we highlight two priorities for operationalizing the AI4ESS framework: strengthening capacity within the ESS community to use AI effectively and critically assessing the broader cost-benefit implications of AI adoption across social, ecological, and economic dimensions.

Responsible AI development in ESS must address misinformation, energy consumption, and data bias through sustained collaboration between domain experts and AI researchers (Nishant et al., 2020). Domain-specific expertise is essential for interpreting complex socio-ecological data, validating AI outputs, and identifying risks associated with biased or non-representative training data, flawed modeling strategies, and societal concerns related to consent, environmental impact, and marginalization, particularly in developing countries (Glessmer and Forsyth, 2025; McGovern et al., 2022). We therefore call for a mutually beneficial synergy that strengthens cross-disciplinary collaboration between AI and ESS, building on the collaborative principles advanced within the AIXES (AI in Earth Sciences) paradigm (Chen et al., 2024).

We propose a four-dimensional AI4ESS framework that jointly addresses challenges, ethical aspects, data and models, and opportunities for advancing AI integration within ESS. These dimensions reflect the main themes that emerged during the expert dialogue sessions described in Section 2, particularly concerning transparency, governance, data practices, and the equitable use of AI in ES research. In contrast to existing paradigms such as GeoAI and AIXES, the AI4ESS framework explicitly extends beyond technical or geospatial modeling to integrate ethical, governance, and inclusivity dimensions. While GeoAI primarily emphasizes the automation of spatial ES assessments through ML and remote sensing, and AIXES focuses on strengthening collaboration between AI and Earth science communities, AI4ESS brings these perspectives together within a single transdisciplinary structure. It situates technical innovation within social and ethical accountability, emphasizing transparency, interpretability, and equitable participation in AI-based ESS applications. This broader framing positions AI4ESS as a community-grounded framework that bridges data, ethics, and decision-support processes to foster trustworthy and sustainable AI integration in ecosystem science.

To ensure applicability beyond conceptual guidance, the AI4ESS framework operationalizes its four dimensions as procedural considerations. These considerations can be applied across the lifecycle of AI-based ES assessments, from data collection and model development to interpretation and policy use. "Challenges" are operationalized by explicitly identifying contexts in which AI methods are appropriate (e.g., large-scale biophysical pattern detection) and those in which human judgment or participatory approaches remain indispensable, particularly where ES values are contested or governance-sensitive. "Ethics" are implemented through community-driven co-design processes rather than fixed normative rules. In practice, this involves engaging ES researchers, Indigenous and local knowledge holders, and relevant stakeholders at the early stages of model design to jointly define acceptable data sources, modeling assumptions, and the intended uses of AI outputs. Indigenous and local participants play advisory and validation roles by contributing contextual knowledge, identifying culturally sensitive information, and supporting interpretation of model results within local socio-ecological realities. Trade-offs among data privacy, transparency, and research reproducibility are addressed through negotiated agreements that specify data access rights, levels of aggregation, and conditions for data reuse, thereby safeguarding data sovereignty while maintaining scientific credibility. "Data and Models" are implemented through harmonized ontologies, transparent metadata, documentation of uncertainty, and the application of explainable AI techniques to support interpretability and bias detection, particularly in data-scarce regions. "Opportunities" are realized by applying AI as a supporting tool for synthesis, communication, and scenario exploration rather than as a substitute for expert judgment. Together, these measures help ensure that AI4ESS can be adopted incrementally across institutions with differing levels of technical capacity, rather than privileging a narrow set of well-resourced actors.

Building on this ethical foundation, within AI4ESS, equity and inclusion are operationalized through explicit data sovereignty and knowledge-governance safeguards across all framework dimensions. While data sovereignty is often discussed in relation to Indigenous and local knowledge systems, similar governance concerns also apply to researchers, institutions, and other data contributors whose datasets may be reused, aggregated, or incorporated into AI systems without adequate control or recognition. Data sovereignty is therefore achieved by recognizing the rights of local and Indigenous communities to retain control over data originating in their territories and ecosystems. In practice, this involves negotiated data governance arrangements that define who can access data, how it may be used for model training, and under what conditions data or derived products may be shared. Such arrangements may include veto rights over specific uses of sensitive data, requirements for data aggregation or anonymization, and guarantees that AI-derived insights are returned to communities in accessible and decision-relevant forms.

To prevent AI-based models from overshadowing Indigenous and local knowledge systems, AI4ESS emphasizes integrating traditional ecological knowledge as a complementary source of insight rather than a competing input. Safeguards include advisory and validation roles for Indigenous and local knowledge holders during model development and interpretation, explicit documentation of where AI outputs diverge from locally grounded observations, and the use of participatory validation processes to contextualize model results. By embedding these safeguards, AI4ESS treats equity not only as an ethical obligation but also as a means of improving ecological accuracy, as locally grounded knowledge often captures fine-scale ecosystem dynamics and long-term environmental change that are poorly represented in large-scale datasets.

The AI4ESS framework fosters stronger transdisciplinary collaboration and broadens the ESS perspective to explicitly include emerging AI technologies, building upon insights from community dialogues (Fig. 1). Based on this foundation, we envision two implementation phases: (1) responsible and ethical development of data, models, and tools, and (2) integration of these developments into ES assessment and decision-making processes.

Table 1 situates the AI4ESS framework in relation to existing AI approaches in environmental science, highlighting how it extends technical and collaborative paradigms by explicitly integrating governance, equity, and community-driven design.

Effective implementation of the AI4ESS framework requires explicitly addressing barriers related to expertise, infrastructure, and access. Limited familiarity with AI methods among ES researchers remains a key constraint, particularly for early-career scientists and practitioners working outside data-intensive research environments. Within AI4ESS, capacity building is therefore envisaged as a core function of the ESP AI-ESS Working Group. Practical mechanisms include targeted training activities (e.g., short courses, summer schools, and online modules), shared methodological notebooks and tutorials tailored to ESS use cases, and open-access AI toolkits designed for non-specialist users. Such initiatives can lower technical barriers while maintaining transparency and methodological rigor.

Computational constraints also represent a challenge to the broader adoption of AI in ESS. As discussed earlier, high-performance computing power and advanced data processing infrastructure remain unevenly distributed, limiting participation by researchers and institutions in low-resource settings. To address this, AI4ESS emphasizes pragmatic solutions such as cloud-based shared computing environments, lightweight and interpretable models that can operate under limited bandwidth or hardware availability, and collaborative platforms that enables models and workflows to be reused rather than rebuilt from scratch (Crowley et al., 2023; Yang et al., 2022). By aligning methodological ambition

Table 1
Comparison of AI4ESS with related AI frameworks in environmental science.

Framework	Key reference	Primary focus	Stakeholder inclusion	Ethics & governance	Equity & local knowledge	Intended application context
GeoAI	e.g., (Karpatne et al., 2019; Zhu et al., 2017)	Automation of spatial analysis and ecosystem mapping using ML and remote sensing	Primarily technical experts	Implicit or limited	Generally not explicit	Large-scale spatial assessment and monitoring
AIXES (AI in Earth Sciences)	(Chen et al., 2024)	Collaboration between AI researchers and Earth scientists	Scientific community	Emerging, not central	Limited	Earth system modeling and analysis
AI for Global Environmental Assessments	e.g., (Baste and Watson, 2021; Ipbes, 2019; Muccione et al., 2024)	Large-scale synthesis for global reporting and scenario analysis	International scientific and policy bodies	Often implicit, top-down	Limited	Global environmental assessments
Community-led AI in conservation	e.g., (Reynolds et al., 2025; Sandbrook, 2025)	Localized conservation decision support	Strong local participation	Context-dependent	Central, but often localized	Site-specific conservation planning
AI4ESS (this study)	This study	Responsible AI integration in Ecosystem Services Science	Researchers, practitioners, policymakers, Indigenous and local communities	Explicit, procedural, and community-driven	Central and operationalized	Ecosystem service assessment, valuation, and decision support across scales

with realistic infrastructure constraints, these approaches support more equitable participation in AI-enabled ES assessments without privileging computational intensity over contextual relevance.

The AI4ESS initiative aims to bridge data gaps, mitigate geographic and linguistic biases, and support the adaptation of ES valuation to diverse policy and governance contexts. The associated working group is intended to support communities, businesses, governments, and researchers by promoting evidence-based decision-making and sustainable practices (Scorza et al., 2023). Outcomes are scalable across multiple dimensions: (i) geographic expansion, with applicability across biomes and ecosystem types and integration of climate-related risk assessments such as flood mitigation and public health benefits; (ii) technological applications, including real-time Earth observation data for dynamic valuation, mobile-first tools for stakeholder engagement, and application programming interfaces for integration with Environmental, Social, and Governance (ESG), financial, and policy systems; (iii) market applications, through interoperability with frameworks such as Taskforce on Nature-related Financial Disclosures (TNFD), Corporate Sustainability Reporting Directive (CSRD), and the Kunming-Montreal Global Biodiversity Framework, supporting use in insurance, banking, policy impact assessment, and carbon market validation; and (iv) knowledge building, including open-source models, value-transfer protocols, and mechanisms for integrating Indigenous and local knowledge. Together, these pathways position AI4ESS as a scalable and inclusive framework capable of supporting more transparent, equitable, and context-aware ES valuation.

5. Conclusion

AI integration into ESS holds great promise but requires governance, transparency, and inclusivity. The AI4ESS framework distills community insights into four dimensions (i.e., challenges, ethics, data/models, and opportunities) to guide responsible adoption. This synthesis underscores that AI should complement, not replace, expert ecological judgment. Ensuring interpretability and fairness in AI-based ES models requires open data standards, clear metadata, and local contextualization. Ethical use must also prioritize equitable access, representation of diverse knowledge systems, and awareness of AI's environmental footprint. The AI4ESS framework thus serves as both a conceptual and practical foundation for interdisciplinary collaboration. It offers the ESS community a means to advance transparent, explainable, and socially responsible AI applications. By formalizing these insights, this short communication aims to catalyze coordinated efforts toward a shared standard for AI-enabled ecosystem assessment and management, an essential step toward sustainable, data-driven stewardship of nature. Future work should operationalize AI4ESS through pilot projects linking open data platforms and explainable AI tools for ES valuation and governance.

CRediT authorship contribution statement

Thalia Ballell Carl: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Vince van 't Hoff:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Jan Haas:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Pedro Cabral:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Felicia O. Akinyemi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization.

Funding

P.C. was partially funded by the National Natural Science Foundation of China (#42275028), and by national funds through FCT, I.P. (Fundação para a Ciência e a Tecnologia, I.P.), under the project – UID/04152/2025 – Centro de Investigação em Gestão de Informação (MagIC)/NOVA IMS (10.54499/UID/04152/2025, and by the European Union – NextGenerationEU under the project UID/PRR/04152/2025 (10.54499/UID/PRR/04152/2025).

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.

Acknowledgements

We gratefully acknowledge the participants in the breakout discussions during the inaugural AI & ES session at the 5th ESP Europe Conference and the 11th ESP World Conference. Their insights laid the groundwork for this community perspective and the development of a dedicated ESP working group.

Data availability

Data will be made available on request.

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Glossary

Meta-AI data: Information describing the inputs, assumptions, training processes, and performance characteristics of AI models, used to support transparency, interpretability, and responsible reuse.

Value-transfer protocols: Methods for transferring ES valuation information from well-studied contexts to data-scarce regions, based on documented assumptions, contextual similarity, and uncertainty considerations.

Explainable Artificial Intelligence (XAI): A set of techniques designed to make the behavior and outputs of AI models interpretable to human users, particularly non-technical stakeholders.

Data sovereignty: The principle that data originating from specific territories or communities should remain subject to locally defined governance, access, and use conditions.