The first systematic map of evidence syntheses on the use of artificial intelligence in ecology

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Abstract

Artificial intelligence (AI) is increasingly used in ecology to automate data-intensive tasks, from species identification and environmental monitoring to ecological prediction. As primary studies have proliferated, evidence syntheses reviewing AI applications have also increased, but their thematic coverage, methodological emphasis, and reporting transparency remain unclear. We conducted a systematic map, critical appraisal, and bibliometric analysis of 72 evidence syntheses published between 2017 and 2025 on AI applications across the broadly defined field of ecology. Synthesis coverage was strongly concentrated on supervised machine learning and deep learning, particularly image-based classification and prediction workflows. In contrast, reviews of AI applications using acoustic, video, sensor time-series, and multimodal data were comparatively scarce. Explicit comparisons between AI methods and conventional statistical or ecological approaches were rare, as was the synthesis of performance moderators such as data availability, class imbalance, transferability, interpretability, and computational cost. Reporting transparency was generally low to moderate, with recurrent shortcomings in protocol availability, screening and extraction reporting, search validation, language coverage, and sharing of data or code. Bibliometric analyses further indicated uneven geographic representation among authors and collaboration networks. Overall, the review literature on AI in ecology is expanding rapidly, but remains better at cataloguing applications than at evaluating when, why, and under what conditions AI methods improve ecological inference or practice. More transparent, reproducible, geographically inclusive, and benchmark-oriented reviews are needed to support robust and decision-relevant ecological informatics.

Keywords— Artificial intelligence; Machine learning; Deep learning; Ecological informatics; Evidence synthesis; Systematic map; Research synthesis; Reporting quality; Benchmarking; Geographic bias

1 Introduction

Artificial intelligence (AI) methods are increasingly used across scientific disciplines to automate complex, repetitive, or analytically demanding tasks (Krizhevsky et al., 2012; Vaswani et al., 2017; Christin et al., 2019). In ecology, this shift is especially consequential because ecological research now generates data at scales and levels of complexity that often exceed traditional manual workflows. From millions of camera-trap images (Christin et al., 2019), and long-term passive acoustic recordings (Pelanda and Diógenes, 2025), to high-resolution remote-sensing products (Wang et al., 2024; Xu et al., 2025; Suleman and Khaiter, 2025), individual-level tracking data (Tiwari et al., 2023), and environmental DNA outputs (Katal et al., 2022). Consequently, AI approaches, particularly machine learning (ML) and deep learning (DL), are increasingly adopted across ecological domains: including species identification (Zhong et al., 2024; Cardenas et al., 2024; Amarathunga et al., 2021; Borowiec et al., 2022), habitat classification (Lee et al., 2023), species distribution modelling (Stupariu et al., 2022; Silva et al., 2021), ecosystem assessment (Lee et al., 2025; Hayes et al., 2025), and conservation planning (Liu et al., 2018; Bose et al., 2025). These applications increasingly emphasise scalable monitoring, automated detection, early warning systems, and decision support for biodiversity conservation and environmental management (Miller et al., 2025). At the same time, architectures, workflows, and software tools change quickly, making it difficult for researchers, practitioners, and other evidence users to maintain a clear overview of which methods have been applied, in which ecological contexts, and with what degree of transparency, rigour, and generalisability. For ecological informatics, the key question is therefore no longer simply whether AI can be applied to ecological data, but whether existing evidence can help researchers decide which methods are appropriate, reproducible, transferable, interpretable, and worth their computational cost.

As the primary literature on AI applications in ecology has expanded (Miller et al., 2025; Nitoslawski et al., 2021), so too has the secondary literature that attempts to synthesise it. Evidence syntheses, including systematic reviews (Gough and Oliver, 2012; Haddaway et al., 2015), meta-analyses (Gurevitch et al., 2018), and systematic maps (James et al., 2016), can organise rapidly growing literatures in a transparent, reproducible, and relatively unbiased way, by using predefined eligibility criteria, and reproducible screening and extraction procedures. They are especially valuable in fast-moving and methodologically diverse fields because they can identify where evidence is concentrated, which methods dominate, and where important uncertainties or gaps remain. However, reviews themselves can accumulate to the point that they become difficult to navigate. They may differ in taxonomic, ecological, methodological, or data-type focus; use different terminology, inclusion criteria, and reporting standards; and vary substantially in transparency and reproducibility. As a result, even when many reviews exist, the overall state of knowledge may remain fragmented.

A systematic map of reviews addresses this problem by providing a higher-level synthesis of existing systematic reviews and related evidence syntheses (Biondi-Zoccai, 2016; Nakagawa et al., 2019). In effect, it makes the review literature itself the object of analysis. Such second-order syntheses can reveal patterns that are difficult to detect across individual reviews, including uneven thematic coverage, recurring methodological limitations, geographic and taxonomic biases, and concentrations of effort in particular applications or data streams (Haddaway et al., 2016; James et al., 2016; Miake-Lye et al., 2016). When combined with critical appraisal, they can also assess how transparently and rigorously reviews have been conducted and reported, which is particularly important in AI-related ecology because rapid methodological turnover, inconsistent terminology, and uneven reporting standards may hinder reproducibility, limit updateability, and reduce practical utility. Bibliometric analysis adds complementary insight into who is producing this literature, where it is being produced, and how collaboration is structured across institutions and countries (Aria and Cuccurullo, 2017; Cobo et al., 2011; Qiu et al., 2014; Zupic and Čater, 2015; Fortunato et al., 2018; Pollo et al., 2024). Together, these approaches clarify what the review literature shows, how this body of knowledge has developed, and where important gaps remain.

1.1 Objectives

The present study combines a systematic map of published evidence syntheses, including systematic reviews, systematic maps, meta-analyses, and related forms of evidence synthesis within the "systematic review family" (Moher et al., 2015), with a critical appraisal and bibliometric analysis. For clarity, we refer to this body of literature collectively as evidence syntheses throughout the manuscript. Our objectives were to:

1. Map the thematic and methodological coverage of evidence syntheses on AI applications in ecology, including data types, AI methods, ecological tasks, and areas of under-synthesis.
2. Critically appraise the reporting transparency and reproducibility of the included evidence syntheses, identifying key reporting strengths and shortcomings.
3. Characterise the bibliometric and geographic structure of this body of literature, including authorship, affiliations, countries of origin, collaboration patterns, and citation profiles.

2 Methods

This systematic map adopts a systematic data analysis approach, comprising three procedural steps. First, we registered the project plan as a protocol to ensure transparency and consistency in our methodology (see: https://osf.io/kj8cx/overview). Second, we conducted an extensive literature search in two databases to collate available systematic reviews on the research topic. Finally, we extracted and mapped preregistered data items from the literature, followed by an analysis of the results.

2.1 Deviations and additions to the protocol

We made several minor additions and refinements to the registered protocol to improve the granularity and clarity of data extraction. These changes did not alter the eligibility criteria or the overall aims of the systematic map. Specifically, we:

1. added an "other biology domain" column to the mapping data table to record biological domains not captured by the original "biology domain" options;
2. revised the "AI model category" column so that it captured broad model categories, namely machine learning and deep learning, while moving training paradigms to a separate variable;
3. added an "AI training paradigm" column to record whether the included reviews reported supervised, unsupervised, or reinforcement learning approaches;
4. added a "Not specified" option to the "AI tools/algorithms" column for reviews that did not explicitly identify any AI tools or algorithms;
5. added an "other AI tools/algorithms" column to record methods mentioned by the reviews but not included among the predefined options; and
6. added an "AI tools/algorithms time periods" column to classify the approximate methodological era or recency of the AI tools and algorithms mentioned in each review.

For more, details please refer to Supplementary Table S1.

2.2 Eligibility criteria

We defined the eligibility criteria using the Population, Exposure, Comparator, Outcome, Study type (PECOS) framework (Richardson et al., 1995). For Population, included studies were systematic reviews, systematic maps, or meta-analyses focusing on AI (including ML and DL) applications within the broadly defined field of ecology, encompassing organismal and ecological levels. Reviews were required to report the use of database searches or structured keyword strategies. Reviews focusing exclusively on non-biological systems, human clinical applications, or molecular and cellular biology were excluded. Our Exposure included reviews that explicitly synthesised AI, ML, or DL as distinct computational approaches, including supervised, unsupervised, or reinforcement learning. Reviews that focused solely on traditional statistical methods or on remote sensing without emphasis on AI-based analysis were excluded. Comparator element was not applicable to our study scope. Outcome included reviews reported outcomes such as prediction, classification, clustering, or generation of ecological data. Reviews that focused exclusively on theoretical or software development aspects without applied ecological outcomes were excluded. Finally, for Study type, only peer-reviewed secondary research article (i.e. reviews) were included. Primary research articles, editorials, opinion pieces, and narrative reviews were excluded. Eligible reviews were published in English or Spanish.

2.3 Piloting

We ran a pilot search in Web of Science Core Collection (hereafter referred to as Web of Science) and Scopus (the two databases we searched) and a pilot screening and data extraction during the development of the research protocol. The piloting stages were designed to assess the effectiveness of our workflow. As a first step of the pilot search, ten systematic reviews were manually collected as benchmarks of bibliographic records from Google Scholar and were used to validate the sensitivity of the search strings created for the Web of Science and Scopus databases (see Supplementary Material Section S1). The search strings were able to retrieve all of the benchmarking records successfully.

We also conducted a two-person (Sergio Poo Hernandez, S.P.H., and Eduardo S.A. Santos, E.S.A.S.) pilot of the screening procedure described in our protocol to evaluate our eligibility criteria. We selected a random sample of 100 articles from the Web of Science search results. We first screened this sample based on the titles and abstracts of the papers, resulting in 13 provisionally included articles. For the provisionally included papers from the first screening, we conducted a second screening round based on the full text, from which we included/maintained two papers. Based on these results, we estimated around 60 systematic reviews to be included in our map of systematic reviews. We then did a pilot data extraction using these two papers to test our data extraction variables. After refining our protocol, we registered it on OSF before proceeding to the main literature searches and data extractions.

2.4 Literature searches

We conducted a systematic search of academic literature to identify relevant reviews. Specifically, we searched two databases, Web of Science and Scopus, with no restrictions on publication type or publication date using the full search strings reported in Sections S1.1 and S1.2. One reviewer (S.P.H.) ran literature searches for eligible reviews on both databases on November 28th, 2025. The searches used English terms only, however Spanish-language reviews were eligible. The search strings are included in the Supplementary Material (Web of Science search string in section S1.1, and Scopus search string in section S1.2). The searches resulted in 1,618 articles from Web of Science and 2,257 from Scopus. Potential duplicates were removed using a custom code in Python (provided in https://github.com/pooherna/AIInEcologySystematicMapResources). After removing duplicates, we ended up with 3,479 documents for screening.

2.5 Title and Abstract screening

Given the large number of documents to screen (3,479), we used the auto-label feature from Sysrev (https://www.sysrev.com/) to pre-filter these documents. This step was an addition to our registered protocol and below we provide a detailed description of our modified process. In brief, the auto-label feature allows the user to create prompts for two Large Language Models (LLMs): ChatGPT-4o (OpenAI, 2024) and Gemini 2.5 Flash (Google, 2024). We developed a prompt that helped us filter out most documents deemed to be primary studies (*i.e.*, studies that collect original data) rather than reviews (second-order studies synthesising primary studies - the focus of our systematic map), because the LLMs algorithm was able to correctly label most documents as primary or secondary studies.

The prompt was developed in Gemini, and we used the documents screened in the pilot as our testing data. We uploaded the title and abstract data from all pilot documents to Gemini 2.5 Flash and we tested and refined the prompt asking whether the study was a review until all documents that were selected in the pilot were correctly labelled by the prompt (see Supplementary Table S2). When applied to the full dataset, this procedure excluded 2,185 studies classified as primary research. Thus, the remaining 1,294 documents (27%) were classified as reviews and then subjected to manual screening by human reviewers.

The manual screening was done through the Sysrev platform where we followed a dual-screening process following our pre-piloted decision tree (see Supplementary Figure S1). The first author (S.P.H.) screened all 1,294 documents. For the parallel screening by a second reviewer, all documents were randomly divided among the remaining authors (three groups of 216 records and three groups of 217 records). Any conflicts that arose between the first and second reviewers were resolved by discussion. A total of 284 documents were included after this screening phase (Figure 1).

2.6 Full-text screening

For the full-text screening, we used a similar process to the title and abstract screening. We first collected the PDF documents of the 284 included studies. From this dataset, we had to exclude five documents because we were unable to source the necessary files to conduct the full-text screening, thus leaving us with 279 documents to screen in full-text stage.

Similar to the title and abstract screening, we used the Sysrev auto-label feature to reduce the number of documents we needed to screen manually. Likewise, this step was an addition to our protocol, and we provide a detailed description of our process. For this phase, the prompt we developed aimed to distinguish systematic reviews from non-systematic (narrative) reviews. We ran the prompt in Gemini 2.5 Flash. As with the previous phase, we used the results from our pilot stage to assess the accuracy of the developed prompt. The assessment showed that our prompt (see Supplementary Table S2) correctly labelled all tested documents (100% accuracy). The primary author (S.P.H.) manually checked the excluded documents to ensure the automated process did not exclude any relevant documents.

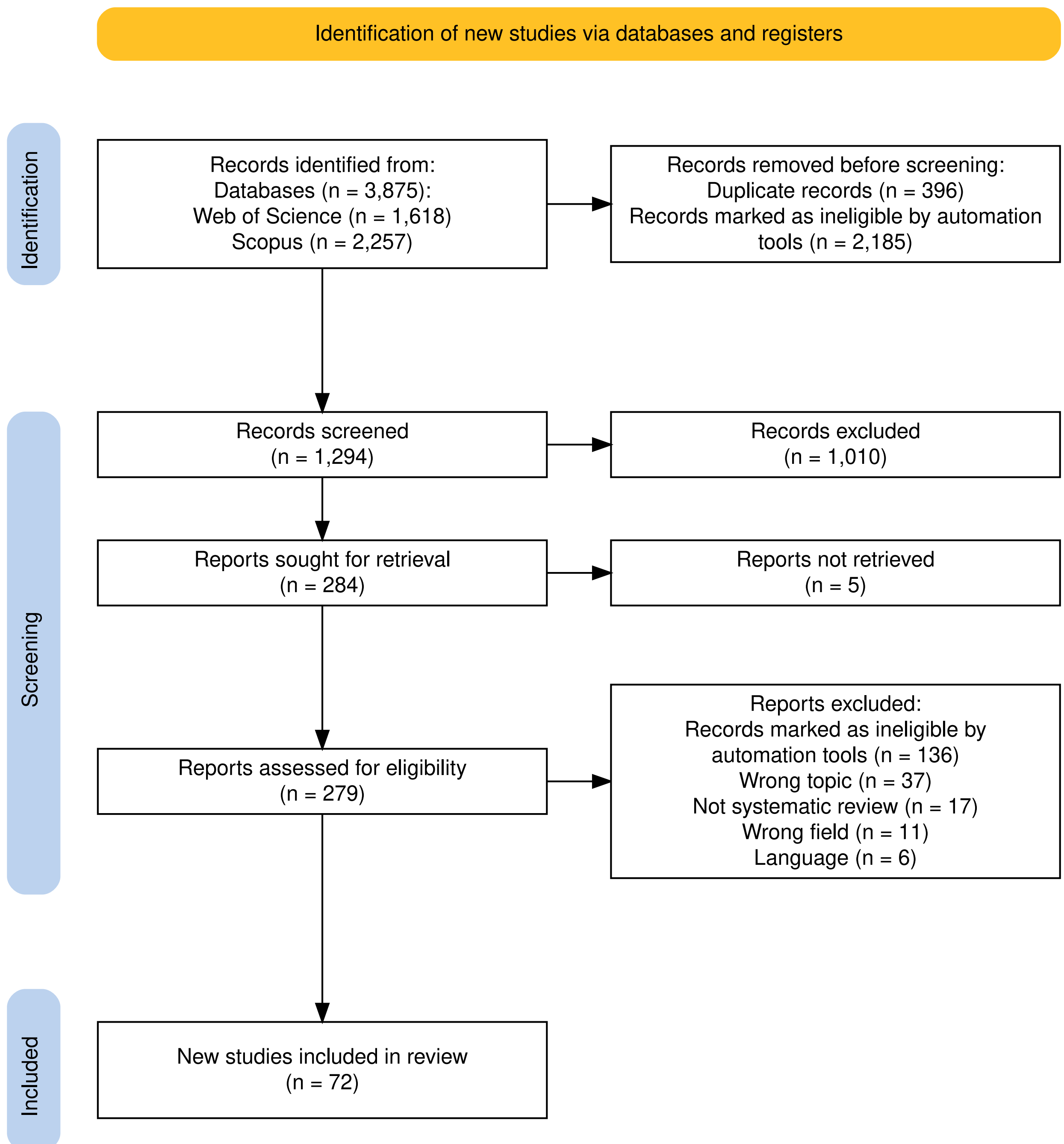

Figure 1: The PRISMA flow-diagram. It shows identification, screening, eligibility, and inclusion stages for systematic reviews of artificial intelligence (AI) applications in ecology. Automated prioritisation (auto-label feature from Sysrev) was used to support screening at both the title/abstract and full-text stages. Created using the PRISMA Flow Diagram tool (Haddaway et al., 2022).

When applied to the full data set of 279 full-text documents, the prompt labelled 143 documents (51%) as likely being systematic reviews, which were then subjected to manual screening by human reviewers.

Manual full-text screening was implemented as a dual-screening process using a registered decision tree (see Supplementary Figure S2). The primary author (S.P.H.) screened all 143 documents. For the second reviewer, all documents were equally randomly divided among the rest of the authors (four groups of 25 records and two groups of 24 records). After screening, we had 22 conflicts, which were resolved between the members that screened that document by discussion, and there was no need for a third member to help resolve the conflicts. A total of 72 documents were included after this screening phase. A summary of the whole screening process is shown in Figure 1.

2.7 Data extraction

We used manual and automatic processes to extract the necessary data from the selected documents. The manual process was performed by S.P.H. using two distinct Google Forms surveys to extract the predetermined items. Extracted data were stored in two tables, organised by data type and linked via unique study IDs. The data tables include two sets of items.

First, for systematic mapping in which data was used for the systematic map covering information on systematic reviews and their scope (Supplementary Table S4), we recorded data on the type of AI algorithms and models mentioned in the review, as well as the tasks they were used for. We also recorded any comparisons that were reported and whether the reviews mentioned any of the factors that influence the algorithms' performance.

Second, for critical appraisal, we employed a modified composite checklist version of the RepOrting standards for Systematic Evidence Syntheses (ROSES) for Systematic Map Reports (Haddaway et al., 2017a) and for Systematic Review Reports (Haddaway et al., 2017b). This checklist focuses on the review method, reporting transparency, limitations, and data and code availability. It consists of 40 questions; for each appraisal item, responses were coded as "Yes", "Partially", "No", or "Not applicable" (Supplementary Table S5). Percentages of each response were calculated using all included reviews as the denominator unless otherwise stated.

The data extraction tables were implemented as Google Forms and converted to Excel sheets for processing. The raw extracted data and the analysis code are publicly available in a GitHub repository (`https://github.com/pooherna/AIInEcologySystematicMapResources`). The metadata (descriptions of data variables) for each table is provided in Supplementary Table S4 for systematic mapping and Supplementary Table S5 for critical appraisal data, respectively. Selected data fields that required more information for the interpretation were accompanied by a dedicated comment field allowing free text entry during the data extraction process. General notes fields were also used to document any additional information that might be of interest for the analysis. The bibliometric data were collected from Scopus using the Digital Object Identifier (DOI) for each individual systematic review included (see Supplementary Table S6).

The automatic data extraction part of the process was done through Sysrev's auto-label feature. Two prompts were developed. The first one was used to extract the names of all AI algorithms and methods mentioned in each document. The second prompt was used to filter documents that contained any analysis of publication trends over time. The results of these prompts were used to complement the manual collection of the key data. Both prompts used Gemini 2.5 Flash and can be found in Supplementary Table S3. As with the prompts used in the screening process, these two prompts were developed and tested using the set of pilot documents, and they correctly retrieved the relevant data from those test documents. Automated extraction was used only to supplement manual coding and did not replace human extraction for the main mapping and appraisal variables.

S.P.H. manually extracted pre-specified data from all 72 documents. To verify these extractions, 10% (n = 7) of the documents were randomly selected for re-extraction by two team members, S.N. (Shinichi Nakagawa), who re-extracted data from 3 documents, and E.S.A.S., who re-extracted data from 4 documents.

2.8 Data mapping and visualisation

We used R version 4.5.2 (R Core Team, 2021) and Python version 3.14.3 (Python Software Foundation, 2026). The bar plots, traffic light plots, and joining of the two bibliometric visualisations were done in Python with the packages *matplotlib* version 3.10.8 (Hunter, 2007), *Pillow* version 12.1.1 (Clark, 2015), *PyMuPDF* version 1.27.2 (Artifex Software, Inc.), and *numpy* version 2.4.3 (Harris et al., 2020). For all other visualisations, including the two bibliometric figures, we used R with the packages *ggplot2* version 4.0.2 (Wickham, 2016), and *circlize* version 0.4.17 (Gu et al., 2014). For the PRISMA plot, we used the PRISMA Flow Diagram tool (Haddaway et al., 2022).

3 Results and Discussion

In the following section we present and discuss the results of our analysis of the 72 included reviews (Christin et al., 2019; Martinez et al., 2025; Zerrouk et al., 2025; Matthews et al., 2025; Lu et al., 2025; Kroth et al., 2025; Kim and Kim, 2025; Wang et al., 2025; Abdenour et al., 2025; Feldmeier et al., 2025; Chimienti et al., 2026; Miller et al., 2025; Cipriano et al., 2025; Chiloane et al., 2025; Axford et al., 2024; Pasanisi et al., 2024; Wang et al., 2024; Kohlberg et al., 2024; Md Jelas et al., 2024; Tiwari et al., 2023; Lazcano-Hernandez et al., 2023; Rubbens et al., 2023; Sharma et al., 2023; Ho and Goethals, 2022; Cruz et al., 2022; Borowiec et al., 2022; Farrell et al., 2022; Hussein et al., 2022; Stupariu et al., 2022; Silva et al., 2021; Nitoslawski et al., 2021; Lürig et al., 2021; Corcoran et al., 2021; Lopez-Marcano et al., 2021; Gobeyn et al., 2019; Dujon and Schofield, 2019; Liu et al., 2018; Weinstein, 2018; Kulicki et al., 2024; Bose et al., 2025; Mkuzi et al., 2025; Gallerani et al., 2025; Liu et al., 2025; Xu et al., 2025; Kyalo et al., 2025; Wu et al., 2025; Suleman and Khaiter, 2025; Morante-Carballo et al., 2025; Khabibullaev, 2024; Özcan et al., 2024; Bao et al., 2024; Zhong et al., 2024; Cardenas et al., 2024; Xu et al., 2024; Ma et al., 2024; Matyukira and Mhangara, 2024; Safonova et al., 2023; Lee et al., 2023; Hirschmugl et al., 2023; Branco et al., 2023; Pillodar et al., 2023; Mulugeta et al., 2024; Kerry et al., 2022; Katal et al., 2022; Amarathunga et al., 2021; Rana and Varshney, 2021; Houinato et al., 2025; Lee et al., 2025; Hayes et al., 2025; Pelanda and Diógenes, 2025; Shivaprakash et al., 2022; Campbell and Vinebrooke, 2025). More details on the included studies can be found in Supplementary Table S7 and a list of excluded studies can be found in Supplementary Table S8. Throughout this section, counts refer to evidence syntheses rather than primary studies unless otherwise stated. Below, we go through our three key objectives in turn.

3.1 Systematic Map of Review Coverage

Evidence syntheses on AI applications in ecology are recent and increasing rapidly. The first included synthesis was published in 2017, with a pronounced increase after 2021 and a peak in 2025 (Figure 2a). The included corpus was dominated by systematic reviews (66 of 72), with five scoping reviews and one meta-analysis, suggesting that synthesis efforts in this area remain largely descriptive rather than quantitatively comparative. Database retrieval trends also indicated faster growth in AI-in-ecology review records than in broader life-sciences review records, with compound annual growth rates of 25.8% and 8.65%, respectively (Figure 2b). This pattern indicates rapidly increasing synthesis attention to AI applications in ecology, consistent with growth in the primary literature reported by several included reviews (Christin et al., 2019; Miller et al., 2025; Nitoslawski et al., 2021).

Review coverage was concentrated around established machine-learning and deep-learning method families (Figure 3a). The most frequently mentioned methods were convolutional neural networks (CNNs; 57 of 72), support vector machines (SVMs; 55 of 72), random forests (55 of 72), k-nearest neighbours (kNN; 34 of 72), and recurrent neural networks (RNNs) (27 of 72). Three reviews discussed AI applications without specifying particular algorithms or model families. These counts should be interpreted as indicators of synthesis coverage rather than direct estimates of method prevalence in the primary literature. Nevertheless, the concentration on CNNs, SVMs, and random forests indicates that reviewers' attention is strongly centred on well-established classification and prediction workflows.

For descriptive purposes, we grouped methods into broad methodological-era categories: classic machine-learning methods, modern deep-learning-era methods, and contemporary transformer- or large-language-model-era methods. These categories are pragmatic descriptors rather than strict historical classifications (Supplementary Table S4). Most reviews covered both classic and modern methods (55 of 72; Figure 3b) while 13 reviews mentioned contemporary transformer- or LLM-era methods. This pattern suggests growing review-level attention to transformer- and LLM-era methods, although most synthesis coverage still focuses on classic and modern machine-learning approaches.

Specific implementations were reported less consistently. Only 35 of the 72 reviews (49%) mentioned named architectures or algorithm implementations, most often neural-network architectures such as ResNet (14 of 72), DenseNet (10 of 72), and AlexNet (8 of 72). Thirteen reviews also mentioned domain-specific implementations, including FishFocusNet

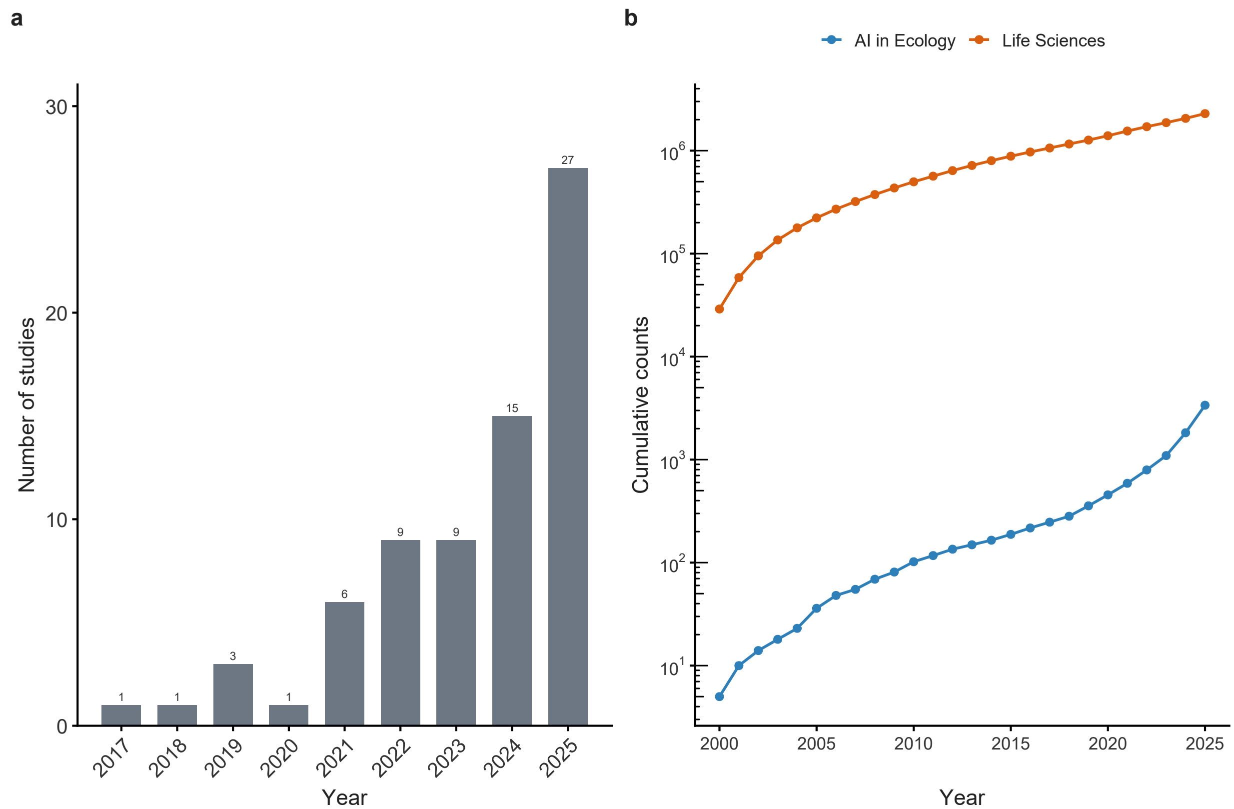

Figure 2: Growth of evidence syntheses on artificial intelligence (AI) applications in ecology. **a**: Number of included reviews by publishing year (total n = 72). **b**: Cumulative number of Scopus-indexed review records retrieved using the AI-in-ecology search strategy compared with cumulative review records in the broader life-sciences reference set from 2000 to 2025. Counts in Panel **b** are based on database retrieval totals from Scopus exports and are not the final screened set of included evidence syntheses. The y-axis in Panel **b** is shown on a $\log_{10}$ scale to allow comparison of growth trajectories across bodies of literature that differ substantially in absolute size.

(Lu et al., 2025), CoralNet (Rubbens et al., 2023), Birdnet (Pelanda and Diógenes, 2025). However, the reviews rarely reported implementation-level details such as model settings, hyperparameters, training procedures, data pipelines, or validation workflows. This limits the extent to which the review literature can support reproducible implementation, cross-study comparison, or method transfer across ecological contexts.

The most frequently reviewed task categories were classification and prediction/regression (Figure 3c). Among the pre-specified task categories, 42 reviews focused on a single category, 28 covered combinations of categories. Classification was covered in 52 reviews, including 24 that focused exclusively on classification tasks. Common examples included species classification/identification (Chimienti et al., 2026; Corcoran et al., 2021; Dujon and Schofield, 2019; Weinstein, 2018; Kulicki et al., 2024; Wu et al., 2025; Zhong et al., 2024; Cardenas et al., 2024; Mulugeta et al., 2024; Amarathunga et al., 2021) and remote-sensing-based monitoring (Kerry et al., 2022; Safonova et al., 2023; Sharma et al., 2023; Lazcano-Hernandez et al., 2023). Prediction/regression was the next most frequently covered task category, appearing in 44 reviews, including 18 reviews focused only on prediction/regression. Examples included species distribution modelling (Pasanisi et al., 2024; Silva et al., 2021; Gobeyn et al., 2019), forest fire prevention (Liu et al., 2025; Bao et al., 2024), and ecosystem-changes prediction (Lee et al., 2025, 2023; Morante-Carballo et al., 2025; Liu et al., 2018). Other task categories were reviewed much less frequently: clustering appeared in six reviews, while dimensionality reduction and data generation each appeared in only one review (Hussein et al., 2022). Two of the reviews covered task types not anticipated in our protocol, namely text mining (Farrell et al., 2022) and digital platforms for scientific collaboration (Khabibullaev, 2024).

Review coverage was strongly concentrated around image-based data (Figure 4a). Image data were covered in 59 of the 72 reviews, including 25 reviews that considered only image-based inputs and 34 that considered image data alongside other modalities. Numeric data were covered in 40 reviews, usually in combination with image data, whereas audio and video data were reported in only eight and two reviews, respectively. Data sources were less consistently described (Figure 4b). Forty-six reviews reported some information on data source, most often field-collected data or combinations of field data with public or private repositories (35 of 72 reviews). Ten reviews focused only on repository-derived data, while 26 did not clearly specify data sources. Remote-sensing reviews tended to provide more specific source information, with LANDSAT (Earth Resources Observation and Science (EROS) Center, 2020) and SENTINEL (European Space Agency, 2025) repositories covered in 20 reviews. Dataset-related limitations, including data availability, bias, and standardisation, were mentioned in 28 reviews, especially in relation to training deep-learning models.

Taken together, these patterns indicate that the review literature is heavily oriented toward image-based classification and prediction workflows. This emphasis is consistent with the prominence of CNNs and other methods commonly used in computer vision, as well as with the use of feature-based image representations in classical methods such as SVMs, random forests, and kNN (Krizhevsky et al., 2012; Chandra and Bedi, 2021; Bosch et al., 2007; Amato and Falchi, 2010). By contrast, reviews less often covered workflows centred on sequential, acoustic, video, movement,

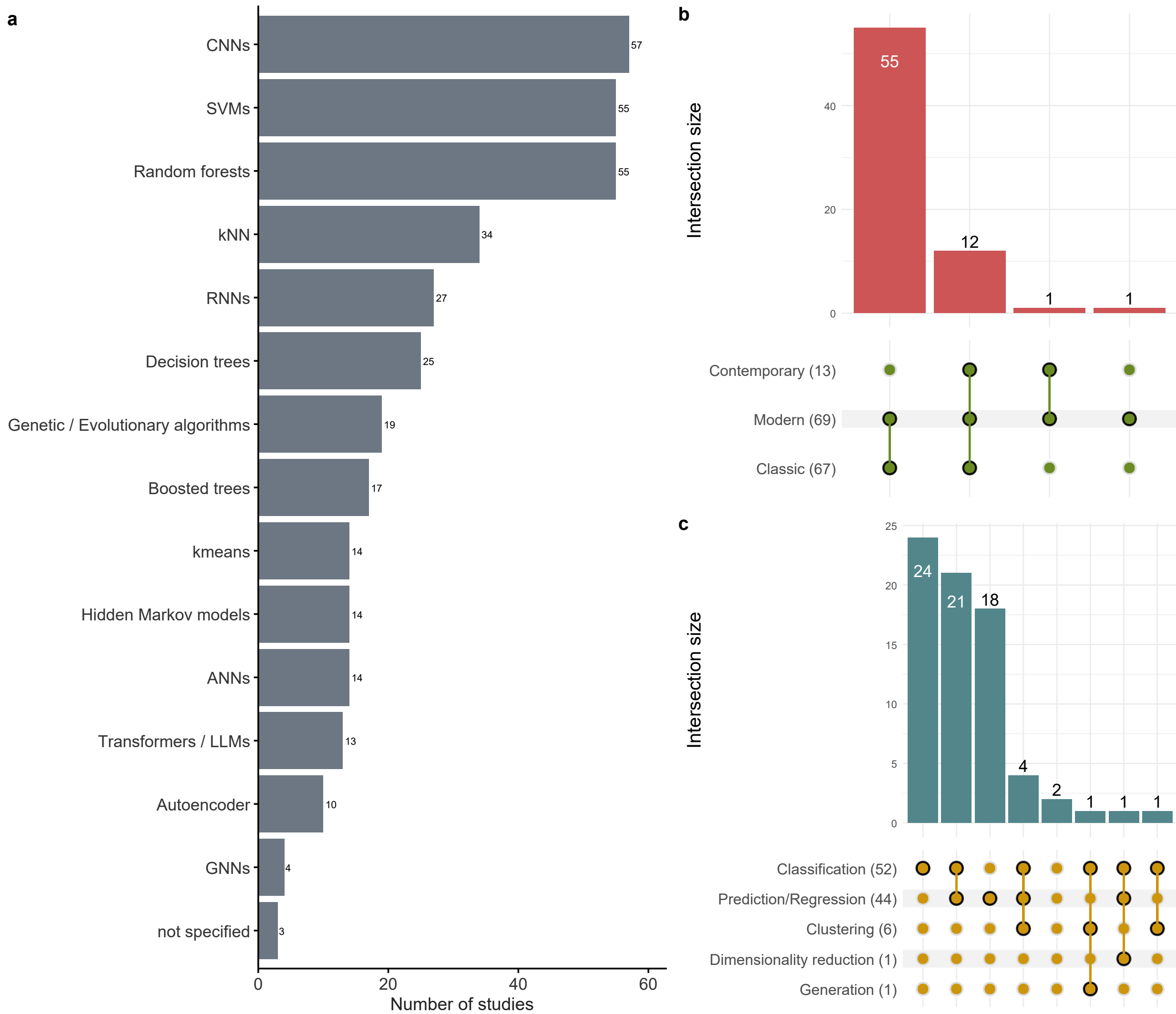

Figure 3: AI methods, broad methodological-era categories, and task types covered by the included evidence syntheses. Counts are at the review level and do not represent the number of primary studies using each method or task type. **a**: Number of evidence syntheses ($n = 72$ total) that mentioned each AI, machine-learning, or deep-learning method after normalising method names to common categories. The "not specified" category indicates reviews that discussed AI methods without naming a specific algorithm or model family. **b**: Co-occurrence of broad methodological-era categories covered by the reviews. These categories are descriptive rather than strict historical classifications: "classic" refers mainly to established machine-learning methods, "modern" to deep-learning-era methods, and "contemporary" to transformer- or large-language-model-era methods. **c**: Co-occurrence of task categories covered by the reviews, including classification, prediction/regression, clustering, dimensionality reduction, and generation. In panels **b** and **c**, bars show the number of reviews covering each highlighted combination of categories; numbers in parentheses show the number of reviews in which each category was recorded.

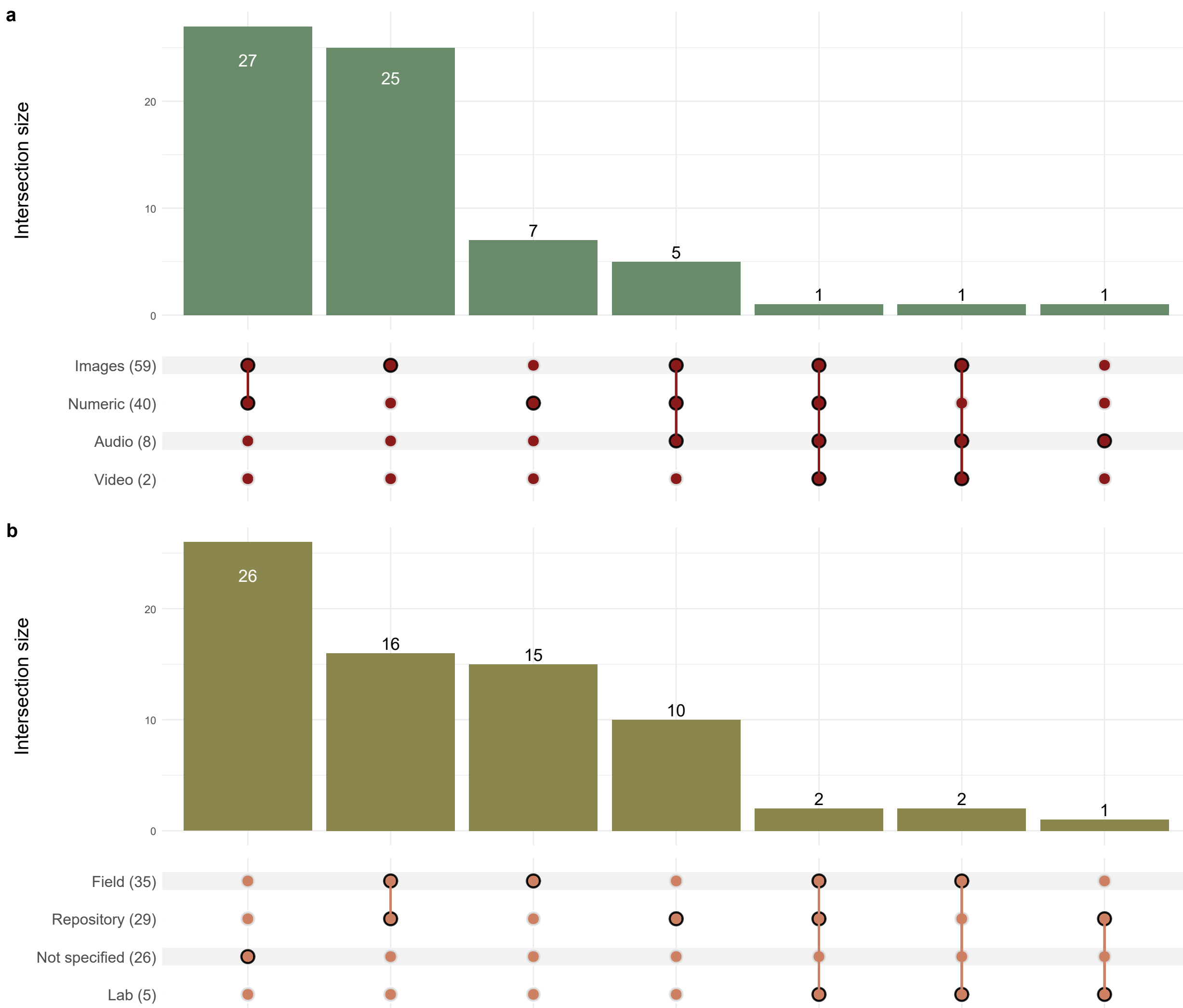

Figure 4: Data modalities and data sources covered by the included evidence syntheses. Counts are at the review level and do not represent the number of primary studies using each data type or source. **a**: Co-occurrence of input data modalities covered by reviews, including image, numeric, audio, and video data. **b**: Co-occurrence of covered data sources, including field-collected data, repositories, laboratory data, and cases in which the data source was not specified. In both panels, bars indicate the number of reviews in each intersection, connected dots indicate the combination of categories represented by that bar, and numbers in parentheses indicate the total number of reviews coded for each category.

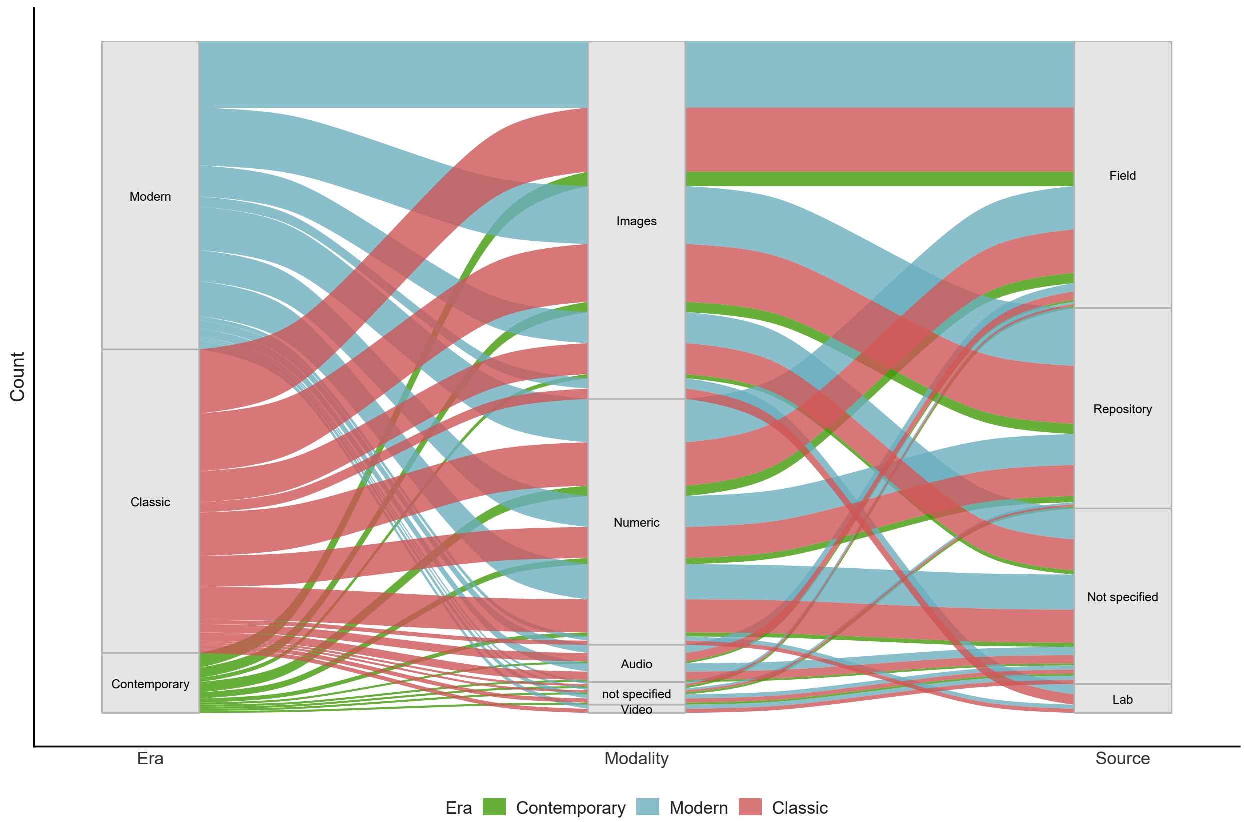

Figure 5: Co-reporting of methodological-era categories, data modalities, and data sources across the included evidence syntheses. Flow widths indicate the number of reviews coded for each combination of broad AI-method era, reported data modality, and reported data source. Colours correspond to methodological-era categories. This figure should be interpreted as a review-level co-reporting map rather than as evidence of direct algorithm–modality–source relationships, because many reviews reported algorithms, data modalities, and data sources separately rather than linking specific methods to specific data inputs and sources.

sensor time-series, or multimodal data, even though these data streams are increasingly important for ecological informatics. RNNs, for example, were less frequently reported than CNNs, which is consistent with the lower review coverage of sequential data modalities such as audio, video, and temporal ecological records (Medsker et al., 2001).

The alluvial summary further illustrates both the breadth and the limitations of the available reporting (Figure 5). Because many reviews discussed algorithms, data modalities, and data sources separately, rather than linking specific algorithms to specific data inputs and sources, it was often not possible to reconstruct method–data–source workflows at a fine level of detail. Thus, Figure 5 should be interpreted primarily as a co-reporting map. This limitation is itself informative: the review literature often catalogues available methods and data types, but provides insufficient granularity to support detailed synthesis of how particular AI methods are implemented across ecological workflows.

A particularly important gap was the limited synthesis of benchmarking and performance moderators. Only three reviews (Martinez et al., 2025; Katal et al., 2022; Campbell and Vinebrooke, 2025) explicitly compared AI methods with conventional statistical or ecological models, such as generalised linear models. Similarly, only nine reviews synthesised factors influencing model performance (Ho and Goethals, 2022; Gobeyn et al., 2019; Xu et al., 2024; Ma et al., 2024; Safonova et al., 2023; Pillodar et al., 2023; Mulugeta et al., 2024; Katal et al., 2022; Campbell and Vinebrooke, 2025) most commonly dataset size, class imbalance, and tuning strategies. Only 1 of those 9 (Ho and Goethals, 2022) described algorithm-specific parameters such as learning rate and regularisation for CNNs or number of clusters for kNN. This limits the ability of the review literature to guide method selection, benchmarking, and decisions about when AI approaches are preferable to simpler or more interpretable conventional methods.

Overall, the mapped evidence syntheses show that AI-related review activity in ecology is expanding rapidly but remains uneven in coverage. Existing reviews are strongest at cataloguing image-based classification and prediction applications, but weaker at synthesising emerging data streams, implementation details, performance moderators, and comparisons with conventional ecological or statistical approaches. As a result, the review literature currently provides a broad overview of AI applications in ecology, but offers more limited guidance on when, why, and under what conditions AI methods improve ecological inference, monitoring, or decision-making.

3.2 Critical Appraisal

Reporting transparency varied widely across the included evidence syntheses (Figure 6a). Because our appraisal was based on published reports and supplementary materials, these results should be interpreted as evidence of reporting completeness rather than direct evidence of how each review was conducted. Overall, most reviews met only a subset of the transparency and reproducibility criteria we assessed.

Language coverage was limited. All included reviews synthesised an overwhelmingly English-language evidence base. Only 23 reviews (32%) explicitly stated that they were only interested in English-language studies and two reviews reported interest in additional languages, such as Spanish, Portuguese, or French, despite using only English search terms (Kohlberg et al., 2024; Nitoslawski et al., 2021). This pattern was reflected in the appraisal items for search-language reporting, intended non-English inclusion, consideration of non-English reviews, and use of non-English search terms (Figure 6). Such language restriction can introduce systematic bias, particularly in biodiversity and conservation research, where relevant evidence may be published in local or regional languages; collaboration with speakers of other languages is one practical way to reduce this bias (Walpole, 2019).

Search reporting was also uneven. Most reviews reported general search terms or keywords (69 of 72; 96%), but only 45 (63%) provided full search strings. This limits reproducibility because bibliographic databases differ in syntax, search fields, and indexing structure, meaning that keyword lists alone are insufficient to reproduce a search. Only 25 reviews (35%) provided a PRISMA- or ROSES-style flow diagram, although 57 (79%) reported the final number of included full-text records. Search validation was rare: only five reviews assessed search sensitivity against benchmark papers or a similar reference set (Axford et al., 2024; Lazcano-Hernandez et al., 2023; Cruz et al., 2022; Hussein et al., 2022; Weinstein, 2018). This is important because insufficient search sensitivity can omit relevant studies and bias synthesis conclusions (Lagisz et al., 2025).

Screening and data-extraction procedures were often under-reported. Only twelve reviews fully described their screening methods, while 23 provided eligibility criteria and a brief overview but omitted key procedural details, such as the number of reviewers involved, whether screening was independent or duplicated, and how disagreements were resolved. Data extraction was similarly under-reported, with only twelve reviews providing a minimally complete description of the process. These omissions limit reproducibility, make it difficult to assess risk of error or bias, and reduce the usefulness of reviews for future updates or second-order syntheses.

Because many (27, 38 percent) included reviews were published in 2025, we compared reporting patterns between reviews published before 2025 and those published in 2025 (Figure 6b and c). The overall proportion of "Yes" responses was similar in both periods (25% in each), suggesting no broad improvement in reporting completeness. Some items improved in 2025, including reporting of competing interests, inclusion of PRISMA- or ROSES-style diagrams, reporting of search languages, and partial reporting of screening methods. For example, competing-interest statements were reported by 93% of reviews published in 2025 compared with 76% of earlier reviews, and PRISMA/ROSES diagrams increased from 22% to 56%. However, other items remained weak or declined, including the provision of metadata, raw extracted data, supplemental files, and analysis or figure code. Thus, recent reviews show greater uptake of some reporting practices but still fall short of open, reproducible synthesis standards.

Our findings are broadly consistent with appraisals of AI-related reviews in other fields and with systematic maps in ecology, which have also identified weaknesses in transparency, reproducibility, and quality-control reporting (Khosravi et al., 2024; Mäkitie et al., 2023; Ricolfi et al., 2024; Mizuno et al., 2025; L. Macartney et al., 2023). These shortcomings are especially problematic in ecological informatics, where rapid methodological turnover makes reviews valuable only if they can be reproduced, updated, and reused. Greater use of preregistered protocols, complete and validated search strategies, transparent screening and extraction workflows, and open sharing of extracted data, metadata, and code would substantially strengthen the reliability of AI-related ecological synthesis.

3.3 Bibliometric Analysis

Authorship was geographically uneven. Based on first-author affiliation, China contributed the largest number of included reviews, with eight records (11%), followed by the United States and Canada (Figure 7a). The most represented countries, including China, the United States, Canada, and Australia, are high-income or highly research-intensive systems according to global economic and development indicators (World Bank, 2024; UNDP, 2025). By contrast, countries from Africa, South-East Asia, Eastern Europe, and Central America were less represented, with 23 of the 72 reviews originating from these regions. Similar geographic patterns have been reported in other systematic

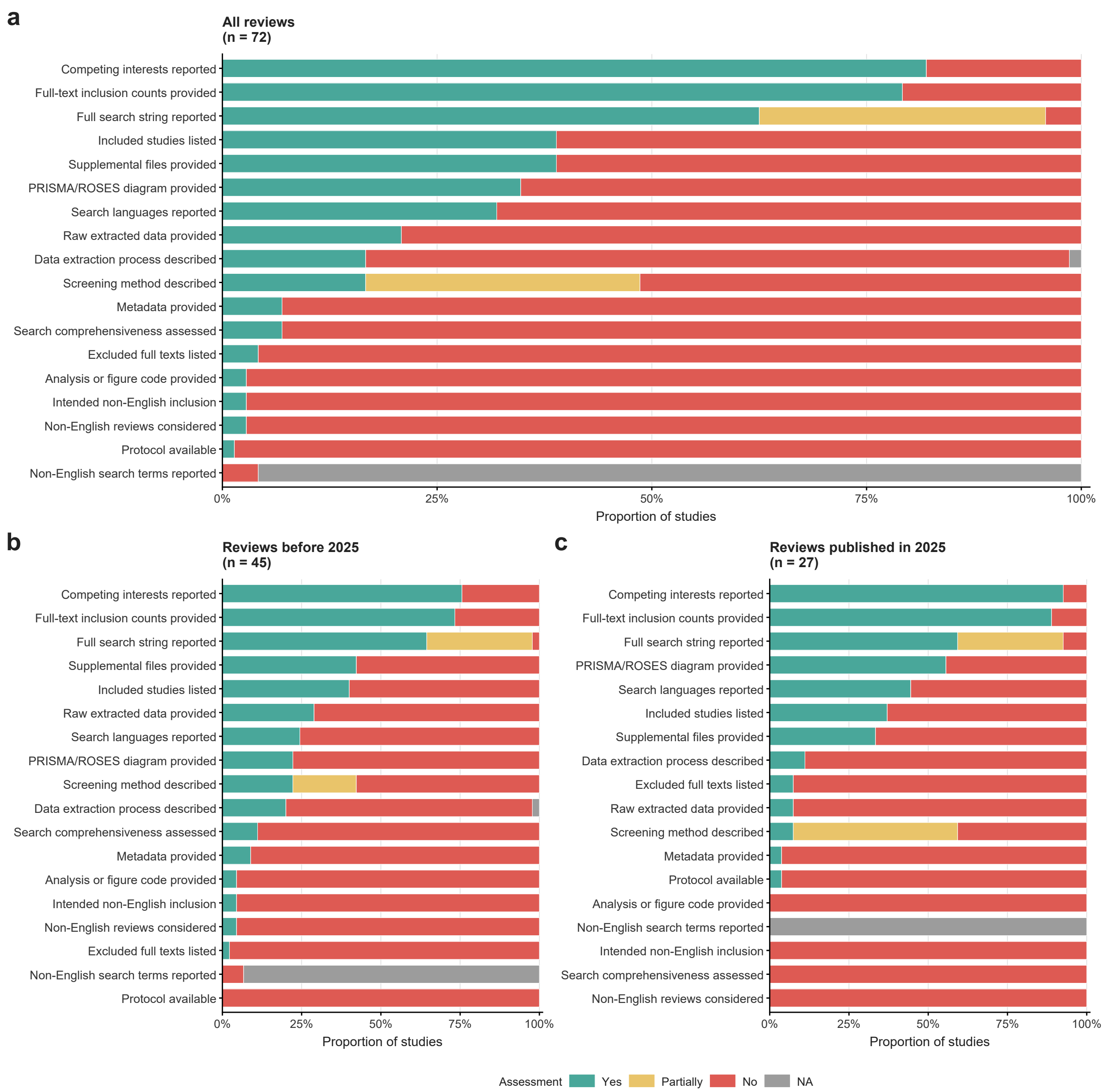

Figure 6: Reporting transparency of the included evidence syntheses based on adapted ROSES appraisal items. Bars show the proportion of reviews coded as fully reported, partially reported, not reported, or not applicable for each item. **a**: Shows all included reviews ($n = 72$). **b**: Shows reviews published before 2025 ($n = 45$). **c**: Shows reviews published in 2025 ($n = 27$). Items are ordered within each panel by the proportion of "Yes" responses. The figure highlights relatively frequent reporting of competing interests, final inclusion counts, and full search strings, but persistent gaps in protocol availability, search validation, non-English-language coverage, screening and extraction transparency, and open sharing of data, metadata, and analysis code.

maps in ecology (Ricolfi et al., 2024; Mizuno et al., 2025; Burke et al., 2023; L. Macartney et al., 2023). Such uneven representation may reflect differences in research funding, infrastructure, training opportunities, collaboration networks, and language barriers (Salager-Meyer, 2008). It also matters because ecological AI applications depend on local biodiversity contexts, monitoring systems, data availability, and environmental-management priorities.

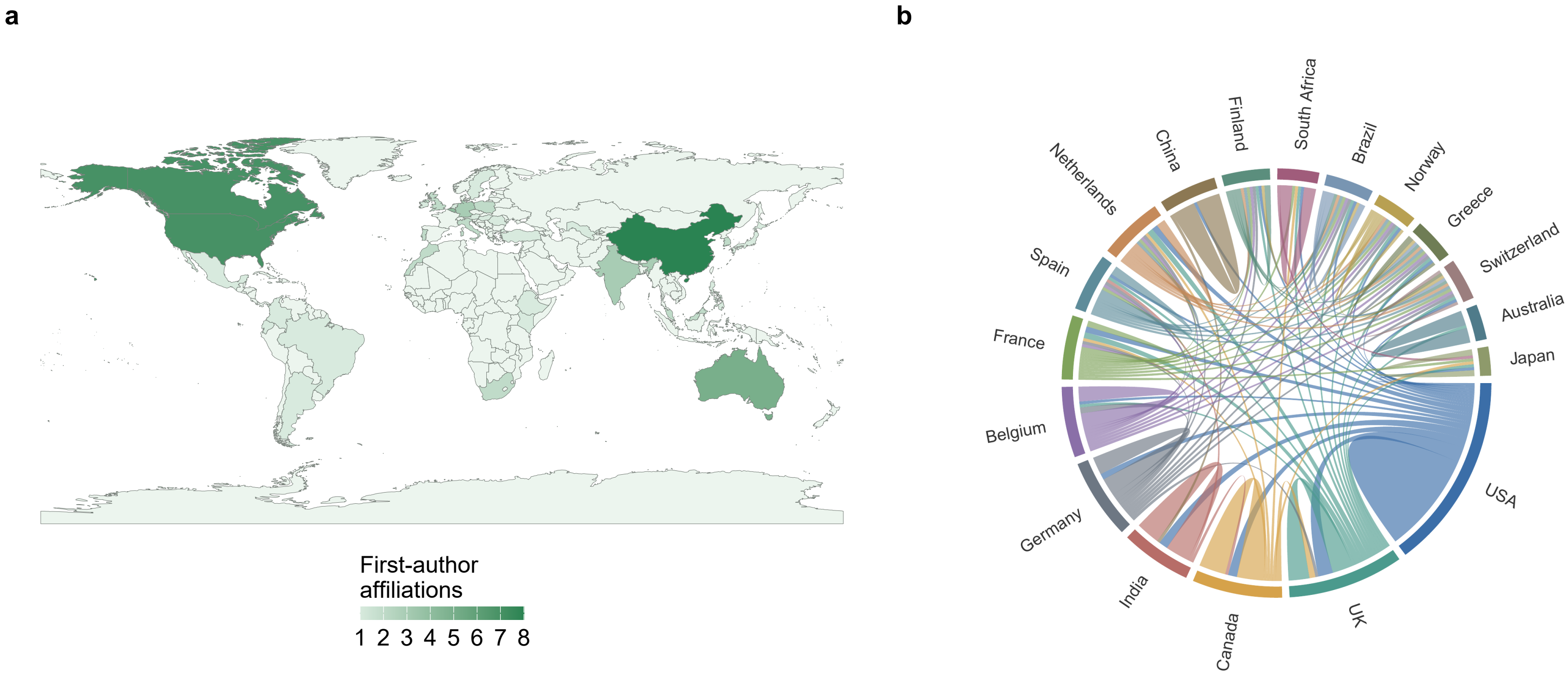

Figure 7: Geographic distribution and international collaboration of authors of included evidence syntheses. **a**: First-author country of affiliation. Shading indicates the number of included reviews associated with each country based on the first author's institutional affiliation. **b**: International collaboration among the 18 countries most frequently represented in the authorship data. Chords indicate co-authorship links between countries based on author affiliations, with wider chords indicating more frequent collaboration between country pairs. Counts in Panel A represent first-author affiliation only, whereas Panel B represents co-authorship links and should not be interpreted as first-author productivity.

Collaboration patterns showed a similarly uneven structure (Figure 7b). The United States had the largest number of collaboration links (67), followed by the United Kingdom (38) and Canada (31). Collaborations involving the United States and Canada were frequent, as were links between North American and European countries. European countries also showed substantial within-region collaboration. Some African countries showed regional collaboration links, including connections among Uganda, Kenya, South Africa, and Ghana, although South Africa also had collaborations with European countries (Supplementary Figure S3). By contrast, regional collaboration among Latin American countries was less visible in our dataset, but this pattern should be interpreted cautiously because the region was under-represented among included reviews. These collaboration patterns broadly align with the geographic patterns reported by some included reviews of primary AI applications in ecology (Wu et al., 2025; Bao et al., 2024; Bose et al., 2025).

Citation patterns were also concentrated. The most-cited review included was (Christin et al., 2019), with 492 citations, reflecting its early and broad role in introducing deep-learning applications to ecology. At the country level, the United States and Canada accumulated the highest citation totals, consistent with their high representation and collaboration activity in the review corpus. These results suggest that influence in the AI-in-ecology review literature is shaped not only by topic and timing, but also by broader geographic and collaborative structures.

3.4 Limitations

Several limitations should be considered when interpreting this systematic map. First, our analyses were conducted at the review level. Therefore, the frequency with which an AI method, task, data modality, or country appeared in our dataset should not be interpreted as the prevalence of that feature in the primary literature. These patterns reflect both synthesis attention and underlying research activity. Second, our searches were conducted using English-language terms, and eligible reviews were limited to English or Spanish. This may have led us to miss relevant evidence syntheses published in other languages or indexed using non-English terminology (Amano et al., 2016, 2021). This limitation is particularly important given the uneven geographic representation and strong English-language dominance observed in the mapped literature. Third, although we tested the LLM-assisted screening prompts during piloting, automated exclusion may still have introduced false negatives. Fourth, our categorisation of AI methods, ecological tasks, data modalities, and methodological eras was necessarily pragmatic; alternative classification schemes could yield somewhat different patterns. Finally, our critical appraisal assessed reporting completeness based on published articles and supplementary materials, and therefore cannot always distinguish between methods that were not conducted and methods that were conducted but not reported.

4 Conclusion and Recommendations

Our findings show that the review literature on AI applications in ecology is expanding rapidly but remains uneven in coverage, transparency, and relevance to decision-making. Existing evidence syntheses are strongest at cataloguing image-based classification and prediction applications, particularly those involving supervised machine learning and deep learning. They are weaker at synthesising emerging data streams, implementation details, performance moderators, and comparisons between AI methods and conventional ecological or statistical approaches. Thus, the main challenge is no longer simply the growth of AI applications in ecology, but the need for more rigorous, reproducible, and benchmark-oriented syntheses of that expanding literature.

Based on our results, we make six recommendations for future reviews on AI in ecology. First, review protocols should be preregistered wherever possible, and any departures from those protocols should be reported clearly, because this would improve transparency, reduce post hoc decision-making, and make future updates easier (Al Shakarchi, 2022). Second, reviews should report full and reproducible search strategies, including complete search strings for each database, all databases searched, any language restrictions, and, where feasible, some form of search validation against benchmark papers or similar checks (Lagisz et al., 2025). Third, screening and data-extraction workflows should be documented transparently, including how many reviewers were involved at each stage, whether screening and extraction were independent or duplicated, how disagreements were resolved, and why studies were excluded at full-text screening, ideally alongside a PRISMA- or ROSES-style flow diagram (Haddaway et al., 2015). Fourth, extracted data, metadata, and analysis code should be shared openly to improve reproducibility, facilitate updates, and increase the long-term value of synthesis efforts. Fifth, future reviews should place greater emphasis on benchmarking and performance-relevant synthesis by more explicitly comparing AI approaches with conventional ecological and statistical methods and by considering moderators such as sample size, class imbalance, transferability, interpretability, and computational cost. Sixth, future work should broaden both thematic and geographic coverage, with greater attention to under-synthesised data types such as acoustics, video, sensor time series, and multimodal workflows, as well as to literature, collaborations, and case studies from underrepresented regions. As AI continues to develop, ecological informatics will benefit not merely from more reviews but from reviews that are transparent, updatable, comparative, and capable of showing when, why, and under what conditions AI methods improve ecological inference and practice.

5 Data Availability

The data and code are available at the GitHub repository: https://github.com/pooherna/AIInEcologySystematicMapResources. They are also archived at the Zenodo repository: https://doi.org/10.5281/zenodo.20647311. A webpage explaining the code used for the Figure generation can be found here: https://github.com/pooherna/AIIn

EcologySystematicMapResources.

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Supplementary material: the first systematic map of evidence syntheses on the use of artificial intelligence in ecology

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S1 Literature searches

S1.1 Web of Science Core Collection search string (November 28th 2025. 1,618 hits)

TS=((“Artificial intelligence” OR “Machine learning” OR “Deep learning” OR “neural network*” OR “Reinforcement learning” OR “Large Language Model*” OR “ChatGPT” OR “machine reasoning” OR “natural language processing” OR “NLP” OR “LLM*” OR “AI/ML” OR “GPT*” OR “machine model*” OR “supervised learning” OR “unsupervised learning” OR “vector machine” OR “classifier*” OR “support vector” OR “topic model*” OR “computer vision”) AND (Ecolog* OR (Evolution* NEAR/3 biology) OR

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biodiv* NOT medic* NOT microb* NOT land*) AND ((“review*” NOT (review* NEAR/3 human)) OR “systematic map*” OR “survey” OR “recent advancement*” OR insight OR meta-analysis OR metareview* OR “meta epidemiolog* review” OR “critical review*” OR “scoping review*” OR “rapid review*”)) AND SU=(“Ecology” OR “Biology” OR “ Evolutionary biology” OR “Biodiversity” OR “Conservation” OR “Life Sciences” NOT “Microbiology” NOT “Physical Sciences”)

S1.2 Scopus search string (November 28th 2025. 2,257 hits)

SUBJAREA (AGRI OR ENVI) TITLE-ABS-KEY ((“Artificial intelligence” OR “Machine learning” OR “Deep learning” OR “neural network*” OR “Reinforcement learning” OR “Large Language Model*” OR “ChatGPT” OR “machine reasoning” OR “natural language processing” OR “NLP” OR “LLM*” OR “AI/ML” OR “GPT*” OR “machine model*” OR “supervised learning” OR “unsupervised learning” OR “vector machine” OR “classifier*” OR “support vector” OR “topic model*” OR “computer vision”) AND (Ecolog* OR (evolution* W/3 biology) OR biodiv* OR conservation) AND (“review” OR “systematic map” OR “systematic surv*” OR “literature surv*” OR “recent advancements” OR insight* OR meta-analysis OR metareview* OR “meta epidemiolog*” OR “meta-epidemiolog*” OR “critical review*” OR “scoping review*” OR “rapid review*”)) AND (EXCLUDE (SUBJAREA,“SOCI”) OR EXCLUDE (SUBJAREA,“ENGI”) OR EXCLUDE (SUBJAREA,“BIOC”))

S2 Tables

S2.1 Deviations and additions to the protocol

Table S1: Deviations and additions from the research protocol

Addition/ Modification	**Description**	**Reason**	**Review stage/ Process impacted**	**Impact's magnitude**
Addition of "other biology domain" column	A new column named "other biology domain" was introduced in the "Mapping" data table.	To record the biology domain if the correct domain is not included in the options in the column named "biology domain".	None	None
Modification to "ai model category" column	The column was modified so that now it records the broad categories of AI models as Machine Learning or Deep Learning, previously it also included training paradigms but those were moved to a new column as described next.	Having AI categories and training paradigms in the same data entry made the data harder to process.	None	None

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Table S1: Deviations and additions from the research protocol

Addition/ Modification	**Description**	**Reason**	**Review stage/ Process impacted**	**Impact's magnitude**
Addition of "ai training paradigm" column	A new column named "ai training paradigm" was introduced in the "Mapping" data table to record what training paradigms the articles mention that the AI tools reviewed use. The included options are supervised, unsupervised and reinforcement learning.	Having AI categories and training paradigms in the same data entry made the data harder to process.	None	None
Addition to the ai tools/algorithms" column	A new options "Not specified" was added to determine an article does not explicitly mention any AI tools or algorithms.	We found some relevant reviews that did not mention specific AI algorithms, so an option was required to code them.	None	None

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Table S1: Deviations and additions from the research protocol

Addition/ Modification	**Description**	**Reason**	**Review stage/ Process impacted**	**Impact's magnitude**
Addition of "other ai tools/algorithms" column	A new column named "other ai tools/algorithms" was introduced in the "Mapping" data table to record the ai tools/algorithms mentioned in the article that are not included in the options in the column named "ai tools/algorithms".	The options we had listed were too limited so we needed a column to specify other algorithms.	None	None
Addition of "ai tools/algorithms time periods" column	A new column named "ai tools/algorithms time periods" was introduced in the "Mapping" data table to record the recency of the AI tools/algorithms mentioned in the article.		None	None.

End of Table

S2.2 Auto label prompts

Table S2: Screening prompts.

Phase	**Prompt**
Title and abstract	Is the article a literature review (such as a narrative review, systematic review, scoping review, or rapid review)? Answer yes if the article is a literature review or if it is unclear. Answer no if the article is clearly not a literature review.
Full-text	Load the file, go through it manually and thoroughly and determine whether it does a search (it can use another term that might indicate a search, for example looked for files, found files) and it also provides a list of terms it used for the search. This can be at any point of the file so read the full file carefully. If you find the information, quote the exact sentence and answer yes. If you do not find it, state 'No search found after scanning all sections' and answer no. Do not assume this must be a systematic review. Do not assume this information is in the Introduction or a in a Materials and Methods section. Follow these instructions with 100% literalness. Do not apply academic conventions or structural expectations. If the information exists in a footnote or a caption it must be included.

End of Table

Table S3: Data extraction prompts.

Data extracted	Prompt
Algorithms	Please perform an exhaustive extraction of every specific technical term related to AI and machine learning from these files. Specifically: Search all sections, including the abstract, methodology, results, tables, and the bibliography/references. List every specific architecture (e.g., ResNet, CNN, VGG), algorithm (e.g., SVM, Random Forest, PCA), software framework (e.g., Detectron2, PyTorch), and specialized tool (e.g., GinJinn) mentioned. DO NOT summarize or use umbrella terms like 'Machine Learning' or 'Deep Learning'—only list the specific name of the method as it appears in the text. Provide the terms in a comprehensive list for each file, and do not omit a term even if it is only mentioned once.
Temporal analysis	For each of the files, load and read each one individually. For each one Mention whether there is a Figure which is a temporal analysis. Mention all Figures that do so.

End of Table

S2.3 Metadata codebook

Table S4: Data to be extracted for Systematic mapping objective

Variable	Description	Format/Allowed values (examples)	Notes
extractor	Initials of the data extractor	Text (*e.g.*, ALM, ML)	For inter-rater calibration and audit trail
study id	Unique ID assigned to the review	Text (*e.g.*, pichler_2023_methods)	Use the first author, the published year, and the published journal
doi	Digital Object Identifier of the review	Text (*e.g.*, 10.1111/2041-210X.14096)	Extract from article metadata

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Table S4: Data to be extracted for Systematic mapping objective

Variable	**Description**	**Format/Allowed values (examples)**	**Notes**
year	Year of publication	YYYY (*e.g.*, 2025)	Extract from article metadata
review type	The main type of secondary review	Systematic review, Systematic map, Meta-analysis	Assign one value based on what the authors explicitly state
mentions n studies	Does the review report the number of primary studies it synthesized after full-text screening?	Yes, No	Must be explicitly reported. If "Yes", record n studies. If "No", leave "n studies" field (next variable) empty
n studies	The number of primary studies synthesized in the review	Integer (*e.g.*, 20)	Must be explicitly reported. Refers to the number of publications, not experiments or effect sizes
biology domain	The primary biological domain(s) of focus	Ecology, Bioinformatics, Systems Biology, Other, Unclear	Multiple categories are allowed
other biology domain	If "other" was selected for biology domain, list the domains here.	Free text (*e.g.*, Forestry)	
data source type	The source of data used in the primary studies reviewed	Field-collected, Lab-generated, Public repository, Unclear	Refers to the origin of the data that ML tools/algorithms are trained on. Multiple categories are allowed

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Table S4: Data to be extracted for Systematic mapping objective

Variable	**Description**	**Format/Allowed values (examples)**	**Notes**
ai model category	Broad category of AI models discussed	Machine Learning, Deep Learning	Multiple categories are allowed. Terms must be explicitly used in the article
ai training paradigm	Training paradigms discussed in the article	Supervised, Unsupervised, Reinforcement Learning	Multiple categories are allowed. Terms must be explicitly used in the article
ai tools/ algorithms	What specific AI tools/ algorithms are reviewed	CNN, RNN, LLM, Decision trees, boosted regression trees, random forest, SVM, other	Multiple categories are allowed. Only some examples are included as categories and can be expanded, if more categories may be required. Terms must be explicitly used in the article
other ai tools/ algorithms	If "other" was selected for ai tools/ algorithms, list them here.	Free text (*e.g.*, kNN, transformers)	
ai tools/ algorithms time periods	Broad categorization based on how recent the AI tools/ algorithms are.	Contemporary, Modern, and Classic	Contemporary is conformed of Transformers and LLMs, Modern includes all Deep Learning algorithms such as CNN, RNN, etc., Classic includes all other ai tools/ algorithms

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Table S4: Data to be extracted for Systematic mapping objective

Variable	**Description**	**Format/Allowed values (examples)**	**Notes**
ai tools/ algorithms comments	Any observations about the AI tools/algorithms listed in the review	Free text (*e.g.*, unclear algorithms)	
specific named tools/ algorithms	Does the review specifies a named tool/algorithm?	Yes, No, Unclear	"Yes" for a focus like "AlexNet" or "AlphaFold"
specific name tools/ algorithms comment	If yes, what specific tools/algorithms are mentioned?	Free text (*e.g.*, AlexNet, ResNet-45, AlphaFold)	List the exact terms used by the authors
compared to stats	Does the review explicitly compare AI tools/algorithms to traditional statistical methods?	Yes, No, Unclear	Yes if there is a direct comparison to methods like linear/logistic regression
application goal	The broad category of the task or goal the AI tools/algorithms are used for	Classification, Prediction/Regression, Clustering, Dimensionality Reduction, Generation, Other	Multiple categories are allowed. This describes what the model is doing
application goal comment	A specific description of the application goals	Free text (*e.g.*, Classifying species from images, Predicting protein structure)	Provide more detail
datatype used	Categories of the data used for the AI tools/algorithms	Audio, Video, Images, Numeric	Multiple categories are allowed
performance moderators	Does the review assess factors that modify or influence AI tools/algorithms performance?	Yes, No, Unclear	"Yes" if the review discusses how things like dataset size, data quality, or hyperparameter tuning affect outcomes

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Table S4: Data to be extracted for Systematic mapping objective

Variable	**Description**	**Format/Allowed values (examples)**	**Notes**
performance moderators comment	If "Yes", name the interacting factors or moderators considered	Free text (*e.g.*, sample size, feature engineering, class imbalance)	List exact terms used
temporal analysis	Does the review do any temporal analysis of the data reviewed?	Yes, No	"Yes" if there is a comparison through time of any of the reviewed data (*e.g.*, the document shows how the number of primary studies focusing on DL has changed over the years). "No" otherwise
temporal analysis comment	If "Yes", what kind of analysis was made	Free text (*e.g.*, Compares number citations of papers using ML through the last decade, compares number of papers using LLMs and number using DNNs in the last 20 years)	List what elements are compared through time
identified gaps	Does the review explicitly identify gaps in the research?	Yes, No, Unclear	"Yes" if the authors state what is missing or needs more work
identified gaps comment	If "Yes", what research gaps are mentioned?	Free text (*e.g.*, Need for more interpretable models, Lack of causal inference methods)	List the exact gaps identified
general notes	Any other relevant comments or observations	Free text (*e.g.*, Main focus was on deep learning, but briefly mentioned classical ML)	Use for important context not captured elsewhere

End of Table

Table S5: Data to be extracted as critical appraisal of included reviews.

Topic	Description	Allowed values
extractor	Initials of the data extractor	Full text (e.g., ALM, ML)
study id	The combination of the first author, the published year, and the published journal.	Full text (*e.g.*, pichler_2023_methods)
doi	Digital Object Identifier of the review	Text (*e.g.*, 10.1111/2041-210X.14096)
supplemental files	If the authors provided any supplemental files, select "Yes"; otherwise, choose "No."	Yes, No
supplemental files note	If you notice anything else that may be relevant, please describe it.	Full text
protocol	The authors provided a citation, DOI, or open access to a published protocol (*e.g.*, "we pre-registered our protocol in OSF (URL)"). If the link has expired or was incorrect, select "No" and add a note.	Yes, No
protocol note	If you notice anything else that may be relevant, describe it here.	Full text
languages mentioned	The authors reported which languages were included in the literature search policy. Select "Yes" if any languages (*e.g.*, English only; English and French) were explicitly stated.	Yes, No
languages mentioned note	List all explicitly mentioned languages used in the review.	Full text
languages non-english	The authors indicated whether they considered non-English studies during the screening process. Select "Yes" if the authors made an effort to include non-English studies, regardless of whether any such studies were ultimately included in the final dataset.	Yes, No
languages non-english note	If you notice anything else that may be relevant, describe it here.	Full text

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Table S5: Data to be extracted as critical appraisal of included reviews.

Topic	**Description**	**Allowed values**
languages non-english included	If the authors explicitly stated that they intended to include any studies in languages other than English in their final dataset, select "Yes".	Yes, No
languages non-english included note	If you notice anything else that may be relevant, describe it here.	Full text
search string english	The authors provided a comprehensive Boolean-style search string and specified the platform for which the string is formatted. If multiple literature databases were used but only one full search string was provided as an example, label it as "Partially." If the authors listed keywords and mentioned the database used but did not provide a complete Boolean string, or provided a search string without specifying search fields, label it as "Partially." If they only listed keywords with no indication of how they were combined or operationalised, select "No".	Yes, No, Partially
search string english note	If you selected "Partially", briefly explain the reason. If you notice anything else that may be relevant, describe it here.	Full text

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Table S5: Data to be extracted as critical appraisal of included reviews.

Topic	Description	Allowed values
search string non-english	The authors reported using non-English search terms or provided search strings formatted for non-English databases as part of their search strategy. If you select "Yes" for the "languages non-english included" column, choose "Yes", "No", or "Partially." If authors provided non-English search terms or complete non-English search strings, and the authors specified the database(s) for which these terms or strings were used, select "Yes". Select "Partially " if any of the following apply: The authors provided non-English search terms or search strings, but did not specify the database(s) for which they were intended. The authors claimed to use non-English database(s), but the search terms they provided (if any) are English only. The authors stated that multiple non-English search terms were used, but only a subset of these terms was reported in the study. Select "No" category if no non-English search terms or search strings were provided. Select "NA" if "languages non-english included" = "No" and multilingual searching is not relevant (e.g., the scope is limited to English-speaking regions).	Yes, No, Partially, NA
search string non-english note	If you notice anything else that may be relevant, describe it here.	Full text
search comprehensiveness	The authors described how the comprehensiveness of the search strategy was evaluated. They should list benchmark papers used to test whether the final search string could retrieve them, ideally with details of this trial-and-error process (*e.g.*, in the supplementary materials). If only one of these elements (either listing benchmark papers or describing the benchmarking process) was reported, code as "Partially".	Yes, No, Partially
search comprehensiveness note	If you select "Partially", briefly explain the reason. If you notice anything else that may be relevant, describe it here.	Full text

Continued on next page

Table S5: Data to be extracted as critical appraisal of included reviews.

Topic	**Description**	**Allowed values**
screening strategy	The authors described how screening and study selection were conducted, including the processes for assessing relevance (at the title, abstract, and full-text screening) and the criteria for inclusion and exclusion (*e.g.*, following PECO/PICO frameworks). A complete description should specify how screening was performed. For multi-author studies, this includes all of: how many screeners participated at each stage of screening (title, abstract, keyword, and full-text), whether screening was conducted under blind (*i.e.*, independently in parallel), how conflicts or discrepancies were resolved (*e.g.*, discussion, consensus, adjudication by a third screener), and any procedures used to maintain consistency among screeners (*e.g.*, double-screening, agreement checking, calibration exercises, pilot screening, or inter-rater reliability). For single-author studies, information on the number of screeners or conflict resolution is not applicable, but the author should still clearly describe how screening and eligible study selection were conducted. If only one of the two core elements (screening criteria or screening process) was described, select "Partially."	Yes, No, Partially
screening strategy note	If you select "Partially", briefly explain the reason. If you notice anything else that may be relevant, describe it here.	Full text
data extraction reproducibility	The authors described the data extraction process (who extracted, double-checking, and consistency). If at least one required aspect is missing, select "Partially." If a single author wrote the synthesis study, assign "NA".	Yes, No, Partially, NA
data extraction reproducibility note	If you select "Partially", briefly explain the reason. If you notice anything else that may be relevant, please describe it.	Full text

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Table S5: Data to be extracted as critical appraisal of included reviews.

Topic	**Description**	**Allowed values**
review flow	The authors reported and visualised the review flow and the number of studies retained at each stage (*e.g.*, in a PRISMA/ROSES diagram). If a complete flow diagram is provided and includes essential elements such as database-level hits, screening numbers, and reasons for exclusion at full-text screening, choose "Yes". If a flow diagram is provided but lacks key components, such as missing database-specific hit counts, missing reasons for full-text exclusions, or incomplete reporting of intermediate steps, select "Partially". If no flow diagram is provided, and the review flow is not described elsewhere in the manuscript/supplemental materials, assign "No".	Yes, No, Partially
review process note	If you notice anything else that may be relevant, describe it here.	Full text
full text screening results	The authors provided the number of studies retained following full-text screening.	Yes, No
full text screening results note	If you notice anything else that may be relevant, describe it here.	Full text
included papers list	The authors provided bibliographic information (for example, author, year, title, DOI) for all studies included in the synthesis. These details may be reported in the main text or in supplemental materials/external repositories (*e.g.*, Zenodo, Figshare, GitHub). In some cases, bibliographic information may be embedded within raw data files rather than presented as a clear list of included studies. If not explicitly stated in the main text check the supplementary files if available.	Yes, No
included papers list note	If "Yes", indicate where you found this information. If you notice anything else that may be relevant, describe it here.	Full text

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Table S5: Data to be extracted as critical appraisal of included reviews.

Topic	Description	Allowed values
excluded papers list	The authors provided bibliographic information for studies excluded at the full-text screening stage, including reasons for exclusion. These details are often reported in supplemental materials/external repositories (*e.g.*, Zenodo, Figshare, GitHub).	Yes, No
excluded papers list note	If "Yes", indicate where you found this information. If you notice anything else that may be relevant, describe it here.	Full text
raw data provided	The authors provided the raw data. If it is missing or the information indicating where the data are located is incorrect (for example, a broken link), assign "No." Data can be found in the main text or in supplemental materials/external repositories (*e.g.*, Zenodo, Figshare, GitHub), depending on how the authors chose to share it. Data can be found in the main text, the supplemental materials, or external repositories (*e.g.*, Zenodo, Figshare), depending on how the authors chose to share it.	Yes, No
raw data provided note	If "Yes", indicate where you found this information. If you notice anything else that may be relevant, describe it here.	Full text
metadata provided	The authors provided the accompanying metadata (variable definitions, coding rules, and descriptions of how each variable was recorded). If metadata is missing or the information indicating where the data are located is incorrect (for example, a broken link), assign "No." Metadata can be found in the main text or in supplemental materials/external repositories (*e.g.*, Zenodo, Figshare), depending on how the authors chose to share it.	Yes, No
metadata provided note	If "Yes", indicate where you found this information. If you notice anything else that may be relevant, describe it here.	Full text

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Table S5: Data to be extracted as critical appraisal of included reviews.

Topic	**Description**	**Allowed values**
code provided	The authors provided analysis and/or figure-generation computer code/scripts. If code/script is missing or the information indicating where the code/script file(s) are located is incorrect (for example, a broken link), assign "No". Code/scripts can be found in the main text or in supplemental materials/external repositories (*e.g.*, Zenodo, Figshare), depending on how the authors chose to share it.	Yes, No
code provided note	If "Yes", indicate where you found this information. If you notice anything else that may be relevant, describe it here.	Full text
competing interests	The authors described any financial or non-financial competing interests or provided a statement declaring none. Note that such statements may appear only in the online version or only in the PDF version, so both should be checked carefully. If they mention they have a conflict/competing interests, copy and paste their statement as a note below.	Yes, No
competing interests note	If "Yes", indicate where you found this information and its content. If you notice anything else that may be relevant, describe it here.	Full text
general note	Any additional notes	Full text

End of Table

Table S6: Data for Bibliometric analysis.

Variable	**Description**	**Format/Allowed values**	**Notes**
doi	Digital Object Identifier of the review	Text (*e.g.*, 10.1111/2041-210X.14096)	Extract from article metadata

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Table S6: Data for Bibliometric analysis.

Variable	**Description**	**Format/Allowed values**	**Notes**
n authors	Number of authors	Integer (*e.g.*, 2)	
authors	Full list of authors	Free text (*e.g.*, Kitzes, J., Poo Hernandez, S.)	
corr country affiliation	Country of corresponding author	Country name (*e.g.*, MEX, CAN)	We will use first country affiliation listed. Follow ISO 3166-1 alpha 3* standard.
first country affiliation	Country of first author	Country name (*e.g.*, MEX, CAN)	Might be the same author as the corresponding author. We will use first country affiliation listed. Follow ISO 3166-1 alpha 3* standard
others country affiliation	Country of the rest of the authors	Country name (*e.g.*, MEX, CAN)	We will use the first country affiliation for all authors. Countries will be listed in the same order as authors are listed in "authors". Follow ISO 3166-1 alpha 3* standard
citations scopus	Citation counts from Scopus	Integer (*e.g.*, 11)	

* List of ISO 3166-1 country codes: https://en.wikipedia.org/wiki/ISO_3166-1

S2.4 Included studies

Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Applications for deep learning in ecology	2019	Christin et al.	Methods in Ecology and Evolution	10.1111/2041-210X.13256
Multimodal data integration to model, predict, and understand changes in plant biodiversity: a systematic review	2025	Martinez et al.	Ecological Informatics	10.1016/j.ecoinf.2025.103485
Machine and Deep Learning for Wetland Mapping and Bird-Habitat Monitoring: A Systematic Review of Remote-Sensing Applications (2015–April 2025)	2025	Zerrouk et al.	Remote Sensing	10.3390/rs17213605
Taxonomic resolution in dual-polarization weather radar observations of biological scatterers: A systematic review	2025	Matthews et al.	Ecosphere	10.1002/ecs2.70419

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Advancing biological taxonomy in the AI era: deep learning applications, challenges, and future directions	2025	Lu et al.	Science China Life Sciences	10.1007/s11427-025-3074-8
Habitat suitability and species distribution modelling in lake macrophyte research: A systematic review	2025	Kroth et al.	Ecological Indicators	10.1016/j.ecolind.2025.114141
AI in extreme weather events prediction and response: a systematic topic-model review (2015–2024)	2025	Kim and Kim	Frontiers in Environmental Science	10.3389/fenvs.2025.1659344
Advancing Nature-Based Solutions with Artificial Intelligence: A Bibliometric and Semantic Analysis Using ChatGPT	2025	Wang et al.	Atmosphere	10.3390/atmos16091102

Continued on next page

Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Toward Sustainable Wetland Management: A Literature Review of Global Wetland Vulnerability Assessment Techniques in the Context of Rising Pressures	2025	Abdenour et al.	Sustainability	10.3390/su17177962
The global threat of wire snare poaching: A comprehensive review of impacts and research priorities	2025	Feldmeier et al.	Biological Conservation	10.1016/j.biocon.2025.111406
Reviewing seas of data: Integrating image-based bio-logging and artificial intelligence to enhance marine conservation	2026	Chimienti et al.	Methods in Ecology and Evolution	10.1111/2041-210X.70063
Artificial intelligence in aquatic biodiversity research: a PRISMA-based systematic review	2025	Miller et al.	Biology	10.3390/biology14050520

Continued on next page

Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Algorithms going wild–A review of machine learning techniques for terrestrial ecology	2025	Cipriano et al.	Ecological Modelling	10.1016/j.ecolmodel.2025.111164
A Summary of Recent Advances in the Literature on Machine Learning Techniques for Remote Sensing of Groundwater Dependent Ecosystems (GDEs) from Space	2025	Chiloane et al.	Remote Sensing	10.3390/rs17081460
Collectively advancing deep learning for animal detection in drone imagery: Successes, challenges, and research gaps	2024	Axford et al.	Ecological Informatics	10.1016/j.ecoinf.2024.102842
A global systematic review of species distribution modelling approaches for cetaceans and sea turtles	2024	Pasanisi et al.	Ecological Informatics	10.1016/j.ecoinf.2024.102700
Remote sensing application in ecological restoration monitoring: A systematic review	2024	Wang et al.	Remote Sensing	10.3390/rs16122204

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
From buzzes to bytes: A systematic review of automated bioacoustics models used to detect, classify and monitor insects	2024	Kohlberg et al.	Journal of Applied Ecology	10.1111/1365-2664.14630
Deforestation detection using deep learning-based semantic segmentation techniques: a systematic review	2024	Md Jelas et al.	Frontiers in Forests and Global Change	10.3389/ffgc.2024.1300060
A scoping review of modelling techniques for ecological connectivity in heterogeneous landscape	2023	Tiwari et al.	Journal of the Indian Society of Remote Sensing	10.1007/s12524-023-01758-1
Algorithms applied for monitoring pelagic Sargassum	2023	Lazcano-Hernandez et al.	Frontiers in Marine Science	10.3389/fmars.2023.1216426
Machine learning in marine ecology: an overview of techniques and applications	2023	Rubbens et al.	ICES Journal of Marine Science	10.1093/icesjms

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
A methodological literature review of acoustic wildlife monitoring using artificial intelligence tools and techniques	2023	Sharma et al.	Sustainability	10.3390/su15097128
Machine learning applications in river research: Trends, opportunities and challenges	2022	Ho and Goethals	Methods in Ecology and Evolution	10.1111/2041-210X.13992
Computer-assisted bioidentification using freshwater macroinvertebrates: A scoping review	2022	Cruz et al.	Water	10.3390/w14203249
Deep learning as a tool for ecology and evolution	2022	Borowiec et al.	Methods in Ecology and Evolution	10.1111/2041-210X.13901
Past and future uses of text mining in ecology and evolution	2022	Farrell et al.	Proceedings of the Royal Society B: Biological Sciences	10.1098/rspb.2021.2721
Applications of computer vision and machine learning techniques for digitized herbarium specimens: A systematic literature review	2022	Hussein et al.	Ecological Informatics	10.1016/j.ecoinf.2022.101641

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Machine learning in landscape ecological analysis: a review of recent approaches	2022	Stupariu et al.	Landscape Ecology	10.1007/s10980-021-01366-9
Modelling invasive alien plant distribution: A literature review of concepts and bibliometric analysis	2021	Silva et al.	Environmental Modelling & Software	10.1016/j.envsoft.2021.105203
The digital forest: Mapping a decade of knowledge on technological applications for forest ecosystems	2021	Nitoslawski et al.	Earth's Future	10.1029/2021EF002123
Computer vision, machine learning, and the promise of phenomics in ecology and evolutionary biology	2021	Lürig et al.	Frontiers in Ecology and Evolution	10.3389/fevo.2021.642774
Automated detection of wildlife using drones: Synthesis, opportunities and constraints	2021	Corcoran et al.	Methods in Ecology and Evolution	10.1111/2041-210X.13581

Continued on next page

Table S7: Included studies.

Title	Year	Authors	Journal	DOI
The slow rise of technology: Computer vision techniques in fish population connectivity	2021	Lopez-Marcano et al.	Aquatic Conservation: Marine and Freshwater Ecosystems	10.1002/aqc.3432
Evolutionary algorithms for species distribution modelling: A review in the context of machine learning	2019	Gobeyn et al.	Ecological Modelling	10.1016/j.ecolmodel.2018.11.013
Importance of machine learning for enhancing ecological studies using information-rich imagery	2019	Dujon and Schofield	Endangered Species Research	10.3354/esr00958
Application of machine-learning methods in forest ecology: recent progress and future challenges	2018	Liu et al.	Environmental Reviews	10.1139/er-2018-0034
A computer vision for animal ecology	2018	Weinstein	Journal of Animal Ecology	10.1111/1365-2656.12780
Artificial intelligence and terrestrial point clouds for forest monitoring	2024	Kulicki et al.	Current Forestry Reports	10.1007/s40725-024-00234-4

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Application of artificial intelligence (AI) for conservation of endangered plant species: a comprehensive review based on global bibliometry	2025	Bose et al.	Biodiversity and Conservation	10.1007/s10531-025-03169-9
A Review of Biomass Estimation Methods for Forest Ecosystems in Kenya: Techniques, Challenges, and Future Perspectives	2025	Mkuzi et al.	Land	10.3390/land14091873
Uncertainties in Modelling Hawaii's Future Precipitation and What It Means for Endangered Forest Birds: A Review	2025	Gallerani et al.	Journal of Biogeography	10.1111/jbi.15121
Advancements in artificial intelligence applications for forest fire prediction	2025	Liu et al.	Forests	10.3390/f16040704

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Progress and limitations in forest carbon stock estimation using remote sensing technologies: a comprehensive review	2025	Xu et al.	Forests	10.3390/f16030449
Automatic synthesis of insects bioacoustics using machine learning: a systematic review	2025	Kyalo et al.	International Journal of Tropical Insect Science	10.1007/s42690-024-01406-2
Advancements and trends in mangrove species mapping based on remote sensing: A comprehensive review and knowledge visualization	2025	Wu et al.	Global Ecology and Conservation	10.1016/j.gecco.2025.e03408
Remote sensing and machine learning in vegetation phenology studies	2025	Suleman and Khaiter	Plant Functional Traits	10.1016/B978-0-443-13367-1.00004-1
Artificial intelligence applications in hydrological studies and ecological restoration of watersheds: A systematic review	2025	Morante-Carballo et al.	Watershed Ecology and the Environment	10.1016/j.wsee.2025.05.004

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Digital economy for biodiversity: Harnessing technology to preserve ecosystems and genetic diversity	2024	Khabibullaev	BIO Web of Conferences	10.1051/bioconf
A comprehensive taxonomy for forest fire risk assessment: bridging methodological gaps and proposing future directions	2024	Özcan et al.	Environmental Monitoring and Assessment	10.1007/s10661-024-12982-8
Research trends in wildland fire prediction amidst climate change: A comprehensive bibliometric analysis	2024	Bao et al.	Forests	10.3390/f15071197
A review: Tree species classification based on remote sensing data and classic deep learning-based methods	2024	Zhong et al.	Forests	10.3390/f15050852
A systematic review of robotic efficacy in coral reef monitoring techniques	2024	Cardenas et al.	Marine Pollution Bulletin	10.1016/j.marpolbul.2024.116273

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
A review of deep learning techniques for detecting animals in aerial and satellite images	2024	Xu et al.	International Journal of Applied Earth Observation and Geoinformation	10.1016/j.jag.2024.103732
Transfer learning in environmental remote sensing	2024	Ma et al.	Remote Sensing of Environment	10.1016/j.rse.2023.113924
Advances in vegetation mapping through remote sensing and machine learning techniques: a scientometric review	2024	Matyukira and Mhangara	European Journal of Remote Sensing	10.1080/22797254.2024.2422330
Ten deep learning techniques to address small data problems with remote sensing	2023	Safonova et al.	International Journal of Applied Earth Observation and Geoinformation	10.1016/j.jag.2023.103569
Data-driven models for predicting community changes in freshwater ecosystems: A review	2023	Lee et al.	Ecological Informatics	10.1016/j.ecoinf.2023.102163
Review on the possibilities of mapping old-growth temperate forests by remote sensing in Europe	2023	Hirschmugl et al.	Environmental Modeling and Assessment	10.1007/s10666-023-09897-y

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
The use of machine learning in species threats and conservation analysis	2023	Branco et al.	Biological Conservation	10.1016/j.biocon.2023.110091
Mangrove resource mapping using remote sensing in the philippines: a systematic review and meta-analysis	2023	Pillodar et al.	Forests	10.3390/f14061080
Deep learning for medicinal plant species classification and recognition: a systematic review	2024	Mulugeta et al.	Frontiers in Plant Science	10.3389/fpls.2023.1286088
An overview of remote monitoring methods in biodiversity conservation	2022	Kerry et al.	Environmental Science and Pollution Research	10.1007/s11356-022-23242-y
Deep learning in plant phenological research: A systematic literature review	2022	Katal et al.	Frontiers in Plant Science	10.3389/fpls.2022.805738
Methods of insect image capture and classification: A systematic literature review	2021	Amarathunga et al.	Smart Agricultural Technology	10.1016/j.atech.2021.100023

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Trustworthy predictive algorithms for complex forest system decision-making	2021	Rana and Varshney	Frontiers in Forests and Global Change	10.3389/ffgc.2020.587178
A comprehensive analysis of the use of modelling and remote sensing techniques for monitoring and managing rangelands	2025	Houinato et al.	Trees, Forests and People	10.1016/j.tfp.2025.101102
A review of assessment methods for coastal hydro-environmental processes: research trends and challenges	2025	Lee et al.	Water	10.3390/w17223278
Remote sensing of grassland plant biodiversity and functional traits	2025	Hayes et al.	Ecology and Evolution	10.1002/ece3.71829
Advances in avian acoustic recognition through artificial intelligence: a systematic review of techniques and environmental applications	2025	Pelanda and Diógenes	Revista Brasileira de Ciencias Ambientais	10.5327/Z2176-94782514

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Table S7: Included studies.

Title	Year	Authors	Journal	DOI
Potential for artificial intelligence (AI) and machine learning (ML) applications in biodiversity conservation, managing forests, and related services in India	2022	Shivaprakash et al.	Sustainability	10.3390/su14127154
Advances in forecasting of harmful algal blooms in freshwater ecosystems	2025	Campbell and Vinebrooke	Environmental Reviews	10.1139/er-2025-0136

End of Table

S2.5 Excluded studies

Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
The applications of complex network analysis in aquaculture and capture fisheries: a systematic review of trends, challenges, and future directions	2025	Vidza et al.	Sustainable Futures	10.1016/j.sftr.2025.101382	Not about AI use in Ecology
Contribution of high-resolution remote sensing to spatial ecology of forest ecosystems at the single tree level: A systematic review	2025	Erfanifard et al.	Remote Sensing Applications: Society and Environment	10.1016/j.rsase.2025.101733	Not about AI use in Ecology
Coral reefs in Vietnam: current state of research and future perspectives	2025	2025	Estuarine Coastal and Shelf Science	10.1016/j.ecss.2025.109554	Not about AI use in Ecology

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Eco-innovation methodologies: a literature review	2025	2025	Discover Sustainability	10.1007/s43621-025-01621-y	Not about AI use in Ecology
Global geoinformation data products for monitoring indicators of Sustainable Development Goals: A review	2025	Hu and Cao	Remote Sensing Applications: Society and Environment	10.1016/j.rsase.2025.101761	Not about AI use in Ecology
Technological advancements: a global review of the use of camera technology in wildlife research	2025	Pollet et al.	Environmental Reviews	10.1139/er-2025-0020	Not about AI use in Ecology
An Ecogeomorphological Approach to Land-Use Planning and Natural Hazard Risk Mitigation: A Literature Review	2025	Zhang et al.	Land	10.3390/land14091911	Not about AI use in Ecology

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Sustainable Digital Economy Transformation Through Intelligent Automation: A Multi-Environmental Framework for Strategic Decision-Making	2025	Kuzior and Sira	Sustainability	10.3390/su17177723	Not in the defined field of interest
Integrating AI models into ecological research workflows: The case of terrestrial bioacoustics	2026	Kitzes et al.	Methods in Ecology and Evolution	10.1111/2041-210X.70133	No search strategy provided
Plastic waste in marine ecosystems: Identification techniques and policy interventions	2025	Das et al.	Water and Soil Pollution	10.1007/s11270-025-08092-x	Not in the defined field of interest

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Global wildlife roadkill research: a bibliometric synthesis of historical trends, thematic gaps, and future directions	2025	Sukhontapatipak et al.	Urban Ecosystemas	10.1007/s11252-025-01747-x	Not about AI use in Ecology
A review of wildlife–vehicle collisions: a multidisciplinary path to sustainable transportation and wildlife protection	2025	Balčiauskas et al.	Sustainability	10.3390/su17104644	Not about AI use in Ecology
A systematic review of machine learning algorithms for soil pollutant detection using satellite imagery	2025	TavallaieNejad et al.	Remote Sensing	10.3390/rs17071207	Not in the defined field of interest

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Advancing sustainable agriculture through bumblebee pollination: bibliometric insights and future directions	2025	Bie et al.	Sustainability	10.3390/su17052177	Not about AI use in Ecology
The Convergence of AI and animal-inspired robots for ecological conservation	2025	Afzal et al.	Ecological Informatics	10.1016/j.ecoinf.2024.102950	No search strategy provided, No search databases provided
The untapped potential of camera traps for farmland biodiversity monitoring: current practice and outstanding agroecological questions	2025	Roilo et al.	Remote Sensing in Ecology and Conservation	10.1002/rse2.426	Not in the defined field of interest

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Evidence on the performance of nature-based solutions interventions for coastal protection in biogenic, shallow ecosystems: a systematic map	2024	Paxton et al.	Environmental Evidence	10.1186/s13750-024-00350-5	Not about AI use in Ecology
Advances and challenges in species ecological niche modeling: a mixed review	2024	Vasconcelos et al.	Earth	10.3390/earth5040050	Not about AI use in Ecology
Beyond observation: Deep learning for animal behavior and ecological conservation	2024	Saoud et al.	Ecological Informatics	10.1016/j.ecoinf.2024.102893	No search strategy provided, No search terms provided

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Automatic detection for bioacoustic research: a practical guide from and for biologists and computer scientists	2025	Kershenbaum et al.	Biological Reviews	10.1111/brv.13155	No search strategy provided, No search terms provided
Advances in remote sensing and machine learning methods for invasive plants study: A comprehensive review	2024	Zaka and Samat	Remote Sensing	10.3390/rs16203781	No search strategy provided, No search terms provided
Long-term spatiotemporal mapping in lacustrine environment by remote sensing: Review with case study, challenges, and future directions	2024	Lai et al.	Water Research	10.1016/j.watres.2024.122457	Not in the defined field of interest

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Unveiling the potential of biomarkers in the context of climate change: Analysis of knowledge landscapes, trends, and research priorities	2024	Zyoud	Regional Environmental Change	10.1007/s10113-024-02246-z	Not about AI use in Ecology
Deep learning in water protection of resources, environment, and ecology: achievement and challenges	2024	Fu et al.	Environmental Science and Pollution Research	10.1007/s11356-024-31963-5	Not in the defined field of interest
Review of the accuracy of satellite remote sensing techniques in identifying coastal aquaculture facilities	2024	Chen et al.	Fishes	10.3390/fishes9020052	Not about AI use in Ecology

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Remote sensing applied to the study of fire in savannas: A literature review	2024	Junior et al.	Ecological Informatics	10.1016/j.ecoinf.2023.102448	Not about AI use in Ecology
Benthic habitat mapping: A review of three decades of mapping biological patterns on the seafloor	2024	Misiuk and Brown	Estuarine Coastal and Shelf Science	10.1016/j.ecss.2023.108599	Not about AI use in Ecology
How have RPAS helped monitor forests and what can we apply in forest restoration monitoring?	2024	Sinegalia et al.	Restoration Ecology	10.1111/rec.14061	Not about AI use in Ecology
Application of artificial intelligence in the study of fishing vessel behavior	2023	Cheng et al.	Fishes	10.3390/fishes8100516	No search strategy provided

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Advances and applications of machine learning and deep learning in environmental ecology and health	2023	Cui et al.	Environmental Pollution	10.1016/j.envpol.2023.122358	Not in the defined field of interest
A review of remote sensing image spatiotemporal fusion: Challenges, applications and recent trends	2023	Xiao et al.	Remote Sensing Applications: Society and Environment	10.1016/j.rsase.2023.101005	Not about AI use in Ecology
A critical review of methods, principles and progress for estimating the gross primary productivity of terrestrial ecosystems	2023	Liao et al.	Frontiers in Environmental Science	10.3389/fenvs.2023.1093095	No search strategy provided

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Remote sensing and invasive plants in coastal ecosystems: What we know so far and future prospects	2023	Villalobos Perna et al.	Land	10.3390/land12020341	Not about AI use in Ecology
Mammal population density estimation using camera traps based on a random encounter model: Theoretical basis and practical recommendations	2023	Ogurtsov	Nature Conservation Research	10.24189/ncr.2023.007	Language
A review of automatic recognition technology for bird vocalizations in the deep learning era	2023	Xie et al.	Ecological Informatics	10.1016/j.ecoinf.2022.101927	No search databases provided
Satellite remote sensing of savannas: Current status and emerging opportunities	2022	Abdi et al.	Journal of Remote Sensing	10.34133/2022	No search strategy provided, No search terms provided

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Spatially explicit capture-recapture through camera trapping: a review of benchmark analyses for wildlife density estimation	2020	Green et al.	Frontiers in Ecology and Evolution	10.3389/fevo.2020.563477	Not about AI use in Ecology
Wildlife-vehicle collisions-Influencing factors, data collection and research methods	2020	Pagany	Biological Conservation	10.1016/j.biocon.2020.108758	Not about AI use in Ecology
Ecological niche models and species distribution models in marine environments: A literature review and spatial analysis of evidence	2020	Melo-Merino et al.	Ecological Modelling	10.1016/j.ecolmodel.2019.108837	Not about AI use in Ecology

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Invasions toolkit: Current methods for tracking the spread and impact of invasive species	2017	Kamenova et al.	Networks of Invasion: A Synthesis of Concepts	10.1016/bs.aecr.2016.10.009	No search strategy provided
A systematic review of modelling approaches and taxonomic focus for studying human wildlife conflict patterns	2025	Kachulu et al.	Discover Environment	10.1007/s44274-025-00425-1	Not about AI use in Ecology
A review of data-driven key technologies for intelligent citrus systems	2025b	Li et al.	Computers and Electronics in Agriculture	10.1016/j.compag.2025.111121	Not in the defined field of interest

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Reimagining soil stewardship in the anthropocene: Nature-positive pathways, pedological perspectives, and land use innovations for soil health and security	2025	AbdelRahman	Soil Security	10.1016/j.soisec.2025.100206	Not about AI use in Ecology
A systematic review of native–invasive pollinator competition in urban green space	2025	Kisvarga et al.	Environmental Challenges	10.1016/j.envc.2025.101219	Not about AI use in Ecology
Research progress on acoustic monitoring of cetaceans		Fengxiang et al.	Biodiversity Science	10.17520/biods.2024556	Language

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Mapping the Structure and Evolution of Fish Bio-and Ecoacoustics; From Single Species Studies to Biodiversity Monitoring	2025	Bolgan	Fish and Fisheries	10.1111/faf.12899	Not about AI use in Ecology
Research Advances in Underground Bamboo Shoot Detection Methods	2025a	Li et al.	Agronomy	10.3390/agronomy15051116	Not in the defined filed of interest
Understanding insect predator–prey interactions using camera trapping: A review of current research and perspectives	2025	Seimandi-Corda et al.	Agricultural and Forest Entomology	10.1111/afe.12646	Not about AI use in Ecology

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Research progress in the intelligent identification of ecologically vulnerable areas and its prospects in the Mongolian Plateau	2025	Meng et al.	Journal of Resources and Ecology	10.5814/j.issn.1674-764x.2025.01.001	Not in the defined field of interest
Evolution and recent trends of Indian oil sardine research: A review	2024	Dash et al.	Ocean and Coastal Management	10.1016/j.ocecoaman.2024.107396	Not about AI use in Ecology
Human-elephant conflict: Understanding multidimensional perspectives through a systematic review	2024	Saha and Soren	Journal for Nature Conservation	10.1016/j.jnc.2024.126586	Not about AI use in Ecology
Forest fire management, funding dynamics, and research in the burning frontier: A comprehensive review	2024	Bargali et al.	Trees, Forests and People	10.1016/j.tfp.2024.100526	Not about AI use in Ecology

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Harnessing artificial intelligence for analysing the impacts of nectar and pollen feeding in conservation biological control	2024	Gurr et al.	Current Opinion in Insect Science	10.1016/j.cois.2024.101176	Not about AI use in Ecology
Machine learning-based design and monitoring of algae blooms: Recent trends and future perspectives–A short review	2024	Sheik et al.	Critical Reviews in Environmental Science anad Technology	10.1080/10643389.2023.2252313	No search strategy provided, No search terms provided
Review of harmful algal blooms (HABs) causing marine fish kills: toxicity and mitigation	2023	Oh et al.	Plants	10.3390/plants12233936	No search strategy provided, No search terms provided

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Forest fuel type classification: Review of remote sensing techniques, constraints and future trends	2023	Abdollahi and Yebra	Journal of Environmental Management	10.1016/j.jenvman.2023.118315	Not about AI use in Ecology
Wildlife monitoring and research using camera-trapping technology across China: the current status and future issues.	2022	Xiao et al.	Biodiversity Science	10.17520/biods.2022451	Language
Forestry big data: A review and bibliometric analysis	2022	Gao et al.	Forests	10.3390/f13101549	Not about AI use in Ecology
Review on methods used for wildlife species and individual identification	2022	Petso et al.	European Journal of Wildlife Research	10.1007/s10344-021-01549-4	No search strategy provided, No search terms provided

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Advances and challenges in modelling the impacts of invasive alien species on aquatic ecosystems	2020	Corrales et al.	Biological Invasions	10.1007/s10530-019-02160-0	Not about AI use in Ecology
Applying various algorithms for species distribution modelling	2013	Li and Wang	Integrative Zoology	10.1111/1749-4877.12000	No search strategy provided, No search terms provided
Recent trends and future directions in artificial intelligence (AI) applications for coastal ecosystems Conservation: Insights from a bibliometric analysis	2026	Cortes	Watershed Ecology and the Environment	10.1016/j.wsee.2025.11.004	Not in the defined field of interest

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Bamboo biomass estimation for sustainable forest management and climate mitigation: a comprehensive review of allometric models and emerging technologies	2025	Tesema et al.	Discover Sustainability	10.1007/s43621-025-02001-2	Not about AI use in Ecology
Large-scale and long-term wildlife research and monitoring using camera traps: a continental synthesis	2025	Bruce et al.	Biological Reviews	10.1111/brv.13152	Not about AI use in Ecology
The evolution of acoustic methods for the study of bats	2021	Zamora-Gutierrez et al.	50 Years of Bat Research: Foundations and New Frontiers	10.1007/978-3-030-54727-1_3	No search strategy provided, No search terms provided

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Table S8: Excluded studies.

Title	Year	Authors	Journal	DOI	Reason for exclusion
Statistical models for the persistence of threatened birds using citizen science data: A systematic review	2020	Wijewardhana et al.	Global Ecology and Conservation	10.1016/j.gecco.2019.e00821	Not about AI use in Ecology

End of Table

S3 Figures

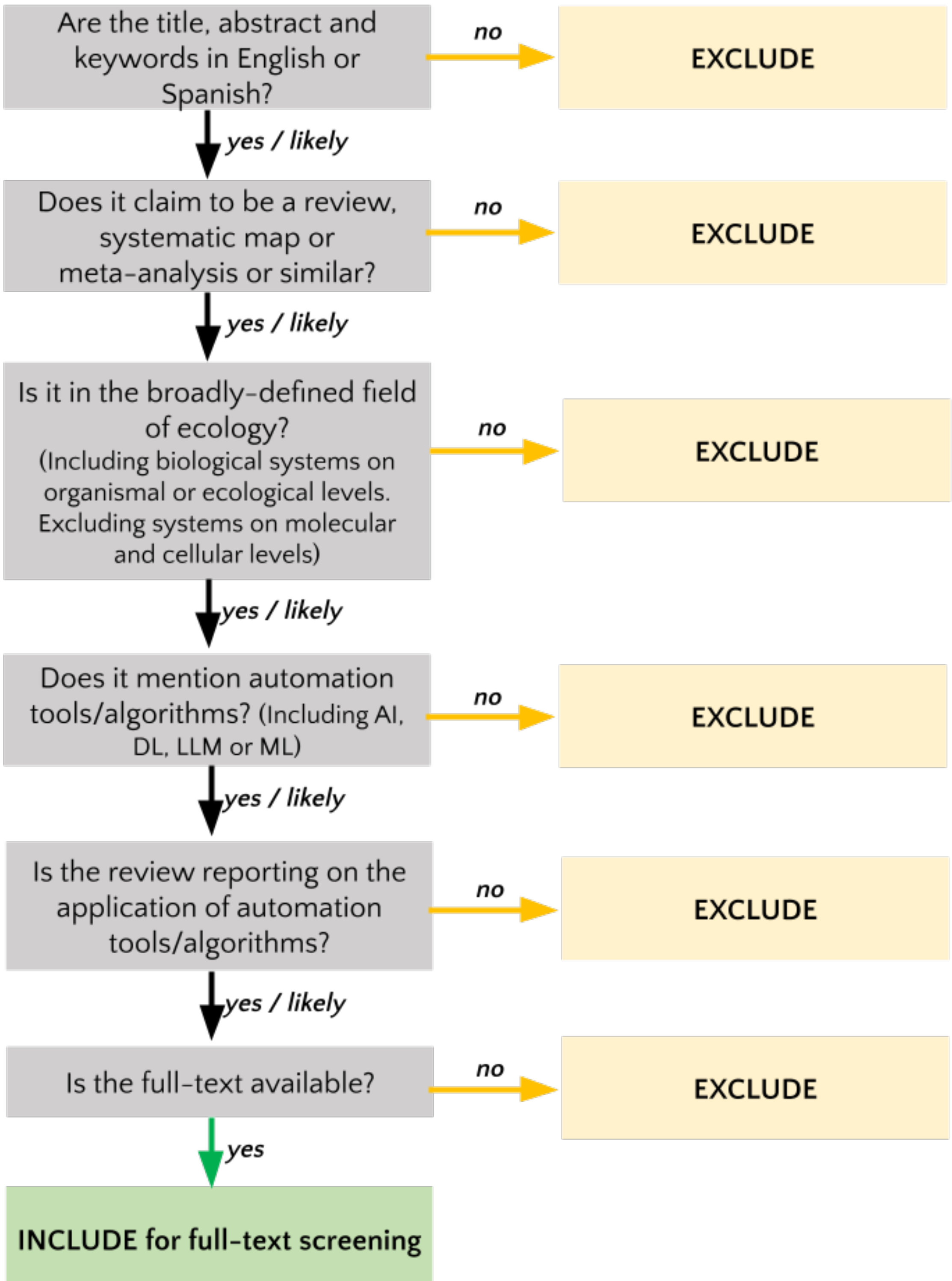

Figure S1: Decision tree that will be used in the Title and Abstract screening phase.

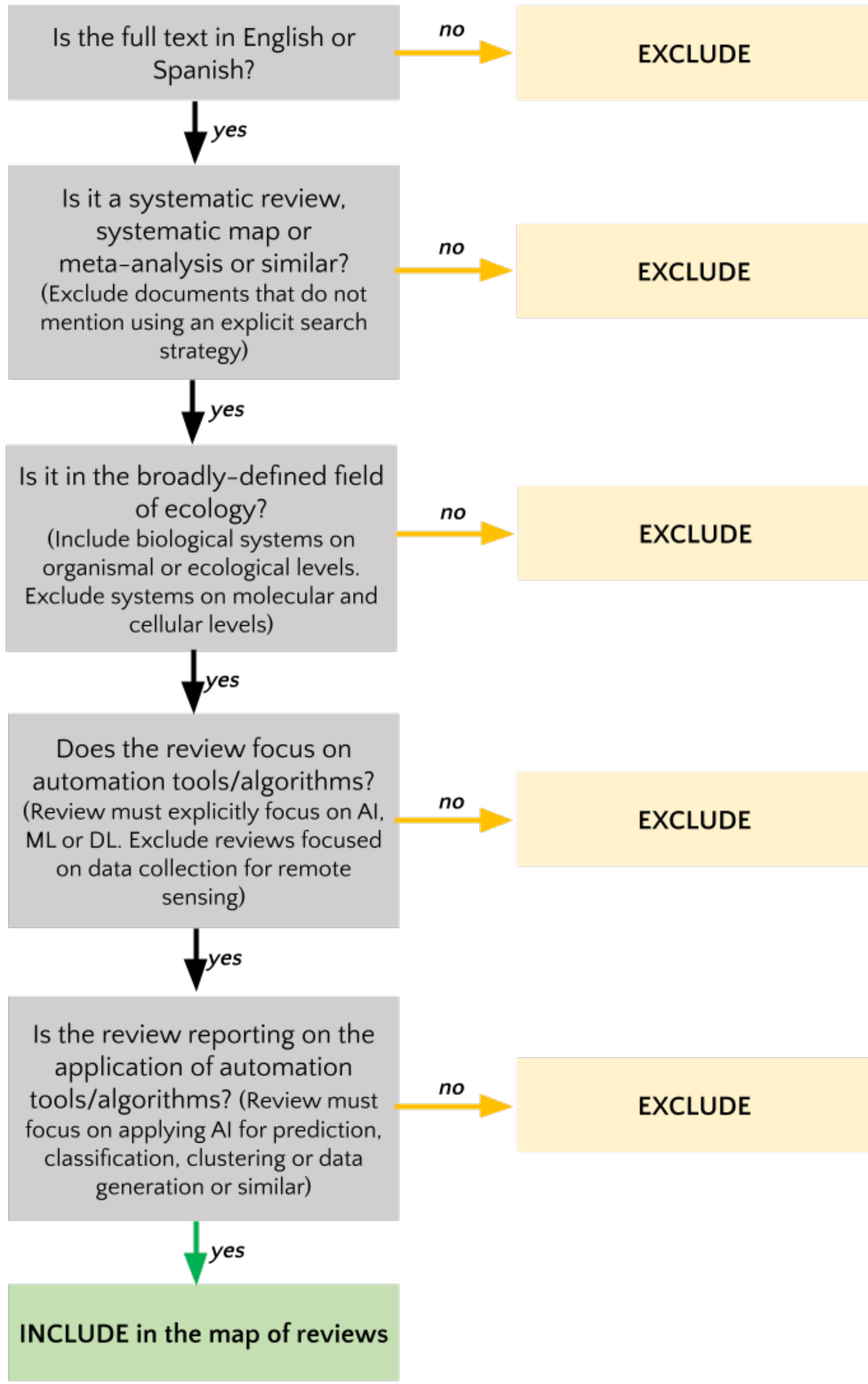

Figure S2: Decision tree that will be used in the Full-text screening phase.

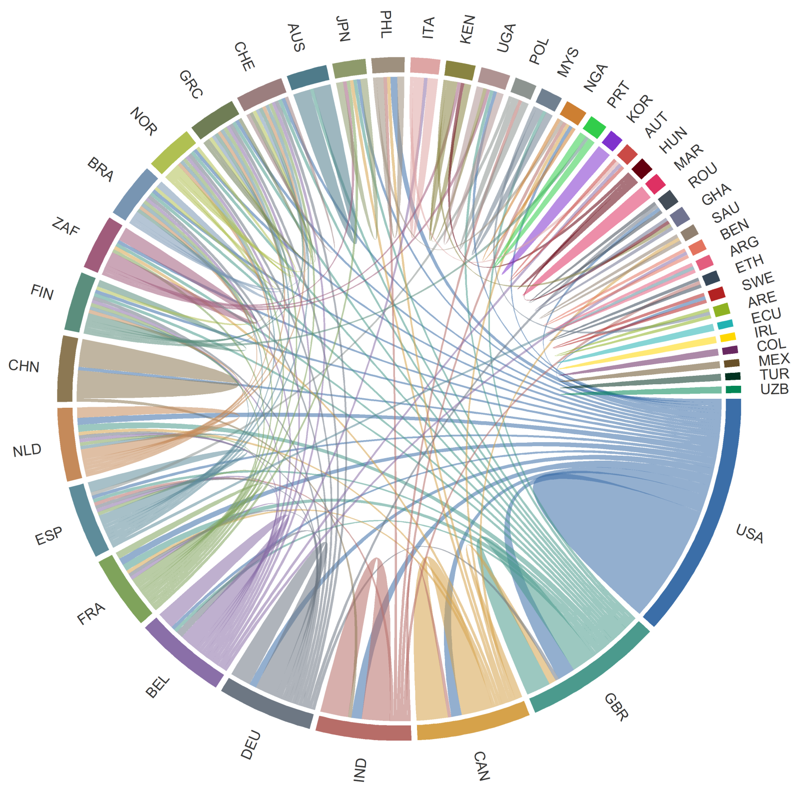

Figure S3: Collaboration across countries.

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