Habitat Intelligence: How Machine Learning Reveals Species Preferences for Ecological Planning and Conservation

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***Abstract*—The emerging confluence between artificial intelligence and ecology has generated a new research frontier, which we refer to as habitat intelligence, aiming to unveil species environment relationships through data-driven approaches. This SLR aims to summarise the pass to the current year (2025) of the research on the use of ML and DL models to represent species preferences, habitat suitability and ecological niches. Based on 365 peer-reviewed papers extracted from SCOPUS, Web of Science and OpenAlex, we identify four main areas of innovation which encompass: automated species identification and ecological monitoring; AI-enhanced species distribution models (SDMs); advanced data collection and processing for ecological research; and conservation-oriented decision support systems. Our review shows that AI has the potential for a more precise and scalable approach to biodiversity investigations in the age of integrated remote sensing, acoustics, citizen science, and environmental data. But we also point out pressing challenges such as data paucity, model interpretability and computational limitations. We suggest that future advancements in this branch of the food web could come from interdisciplinary cooperation using explainable AI (xAI) and the construction of bridging hybrid models between prediction and ecological interpretability. In the end, this review offers a conceptual and methodological 'roadmap' to other researchers and conservation practitioners who wish to apply AI to the service of global biodiversity aims.**

Keywords*—Artificial Intelligence; machine learning; deep learning; species preferences; habitat suitability modeling; Species Distribution Models (SDMs); ecological niche modeling; conservation planning; environmental monitoring; Explainable AI (xAI); habitat intelligence; biodiversity management

I. Introduction

Biodiversity erosion, habitat degradation and the increasing consequences of global climate change represent major challenges for conservation science and environmental management. Knowledge of the preferences that species exhibit for particular habitats (hereafter referred to as species–environment relationships or ecological affinities) is critical to both effective biodiversity conservation,5 ecological forecasting, and spatial planning. Conventionally these preferences are investigated with ecological niche models (ENMs), species distribution models (SDMs), and empirical field observations. However, these methods are often limited by insufficient data, linear assumptions, and difficulty in extrapolation across ecosystems or taxonomic groups.

The past few years have seen accelerating interest in artificial intelligence (AI), and in machine learning (ML) and deep learning (DL) more specifically, in ecology. These approaches provide unparalleled functionality for analyzing complex, non-linear data with high dimensionality, which enable more accurate and higher spatial resolution predictions and models for species' habitat preferences. AI has begun to be applied in diverse fields such as remote sensing and automated ecological monitoring to manipulate patterns from largescale environmental datasets, amalgamate heterogeneous sources of data (e.g., climate, land cover, biotic interactions), and discover ecological patterns that were overlooked or impractical to quantify before.

This nascent field what we will call here "Habitat Intelligence" represents a synthesis of fields: ecological modeling, computer vision, geospatial science, and conservation biology. The increasing amount of works that employ ML algorithms for species preference analysis suggests that a structured research topic has come to the fore, for which no synthesis is nevertheless available. However previous reviews focus on AI applications to biodiversity in general and do not directly analyze modelling species habitat preference across various ecosystems and taxa. This review introduces the concept of habitat intelligence, defined as the integrative use of artificial intelligence techniques to uncover, interpret, and model species–environment relationships for conservation purposes. This emerging field synthesizes ecological modeling, computer vision, geospatial science, and conservation policy. The objective of this paper is to map this interdisciplinary domain through a systematic literature review (SLR) of 365 peer-reviewed studies published between 1996 and 2025. The following sections present the methodology of the review, a synthesis of AI applications across four thematic axes, a discussion of their implications, and key challenges and future perspectives.

The following research questions are considered throughout the review:

- How is AI helping to identify species and monitor the natural world?
- What are the current best machine learning techniques used for the species distribution models (SDM) and habitat suitability models?
- What are the types of data, sources, and preprocessing techniques employed to facilitate artificial intelligence-driven ecology modeling?

- How do AI-based models assist with conservation planning, biodiversity management, and ecosystem resilience?

Through asking these questions and following the IMRAD approach , the current review seeks to chart the intellectual terrain of this fast-developing area, scope current research themes and lacunae, and suggest directions for future interdisciplinary efforts at the AI and conservation science boundary.

II. Related Work

Previous reviews have explored the use of machine learning and deep learning in ecological contexts, including species distribution modeling (SDMs), environmental monitoring, and biodiversity prediction [1], [7], [8], [35]. However, these reviews typically focus on specific techniques or limited ecological domains. None provide a comprehensive synthesis of the integration of AI with ecological preference modeling across data types and ecosystems. Moreover, the conceptual emergence of "habitat intelligence" as a unified research direction has not been formalized. This article addresses this gap by combining methodological mapping, taxonomic classification of AI applications, and a focus on implementation value for conservation and policy planning.

III. Methodology

This study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Figure1 framework to ensure methodological rigor, transparency, and reproducibility. The systematic literature review (SLR) was designed to capture and synthesize scholarly work that applies artificial intelligence(AI) including machine learning(ML) and deep learning(DL) to species habitat preference modeling, species distribution, and conservation planning.

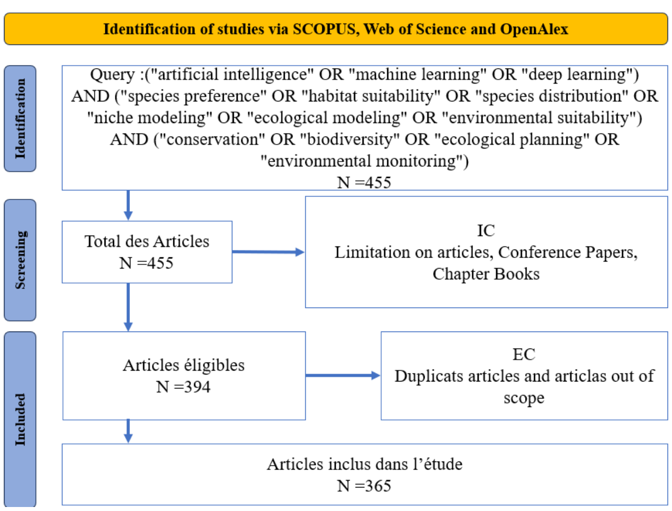

Fig. 1. PRISMA Aproach.

The bibliographic data were collected from three major academic databases: SCOPUS, Web of Science, and OpenAlex. A unified query was applied across all three platforms, targeting articles that addressed the intersection of AI and ecological modeling with a focus on species preference and conservation. The query string was as follows: ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("species preference" OR "habitat suitability" OR "species distribution" OR "niche modeling" OR "ecological modeling" OR "environmental suitability") AND ("conservation" OR "biodiversity" OR "ecological planning" OR "environmental monitoring")

A. Screening Process

The screening was conducted in two main stages:

- Initial Screening (Inclusion Criteria - IC):

The first filter excluded irrelevant publication types such as non-peer-reviewed documents, book chapters, theses, editorials, and workshop summaries. Only journal articles, conference papers, and reviews published in peer-reviewed venues were retained. After this stage, 394 articles were considered eligible.

- Secondary Screening (Exclusion Criteria - EC):

The eligible articles were further examined to remove:

- Duplicate records across databases;
- Articles that did not directly address the use of AI for modeling species preferences or conservation planning;
- Studies focusing on unrelated applications of AI in biology or agriculture without ecological modeling relevance.

After applying these criteria Table1, a final set of 365 articles was retained for full analysis.

TABLE I. Inclusion and Exclusion Criteria for Article Selection

Criteria Type	Description
Inclusion Criteria (IC)	• Peer-reviewed articles using AI/ML/DL for species distribution modeling, habitat suitability, or conservation planning; • Published between 1996–2025; • Indexed in SCOPUS, Web of Science, or OpenAlex.
Exclusion Criteria (EC)	• Non-English articles, duplicates, and non-ecological AI studies; • Articles not focusing on species–environment interactions or habitat modeling.

IV. Results

The intersection of artificial intelligence (AI) and machine learning (ML) with ecological research is a transformative technological advancement that is reshaping how scientists study biodiversity and ecological systems. An aspect of machine learning is deep learning, which is widely used as a fundamental part of ecological data science for interpreting complex patterns not easy to capture using classical statistical methods [1][2]. This technological merging is especially useful in the current era of unprecedented challenges to ecology such as biodiversity loss, effects of climate change, and diseases outbreaks [3].

AI In Ecology The modern wave of AI knowledge and techniques are now being more commonly adopted within ecological research due to the increasing computing power to run standard learning [4]. Machine learning methods are powerful in recognizing complex patterns generated by higher-order interactions and are applied to identify patterns of genetic regulatory networks and patterns of species coexistence [5][6]. These skills have been especially useful in handling the increasingly large data sets produced through automated surveillance of populations and communities [7].

AI based applications in ecological domain cover wide range of applications such as automatic species identification, ecology modeling, behavioral analysis, DNA sequencing, and population genetics [8]. Good the In particular, these technologies support the study of the organism-environment interaction using camera and acoustic, animal behavior using deep learning and satellite data to ecological functions [3]. In the context of the marine environment, AI is contributing to relieve data processing bottlenecks in coral reef surveys by applying machine learning that can efficiently process large quantities of image data [9][10].

One especially exciting use is for overcoming data gaps in conservation status assessments. The conservation status of data deficient species may be inferred using machine learning models that can predict this, and data deficient species for which such models can be developed removed from lists of potential species for which the conservation status is unresolved [1][11]. Ecological niche models have also been advanced and expanded upon through the use of machine learning, informing our understanding of species distributions and habitat suitability and having applications for conservation biology and climate change [12].

With the further development of these technologies, however, they are becoming the most advanced tools available for ecological research, allowing for new methods of monitoring, understanding and conserving biodiversity in the context of global environmental change [3][4].

A. AI Applications in Species Identification and Monitoring

The use of artificial intelligence has changed the strategy of how ecologists discover or track species, deep learning provides us with an efficient method to analyze the massive data produced by recent ecodging monitoring systems [13-15]. The camera trap is one of the most important monitoring technologies that has been revolutionized by AI, which is critical for tracking wildlife distribution and activities at large spatial and temporal scales, showing great potential for wildlife community studies [16][17]. The biggest impediment with camera trap experiments, namely transferring millions of images, is being overcome thanks to the implementation of deep learning techniques, especially for what concearns the Convolutional Neural Networks (CNN), that can automatically identify wild animals and assign them to taxonomic entities with outstanding accuracy [18].

Such AI-based systems show remarkable results in species identification works. Deep neural networks have been demonstrated to automatically recognize animals with more than 93.8% accuracy, andnovel demonstrations validate that networks which are forced to select purely on high-confidence predictions of high confidence are as accurate as human volunteers in identifying taxa (96.6% accuracy) while being more than two orders of magnitude faster, processing thousands of images in less than a second without any training in this taxonomic category [18][19] Figure2. This substantially sped up processing (approximately 2000 images per minute on typical computing hardware) amounts to a revolution in our capacity for ecological research [20]. By incorporating AI with citizen science collaboration, it has been demonstrated that human effort can be minimized by as much as 43% without losing overall accuracy interms of detecting webs [21].

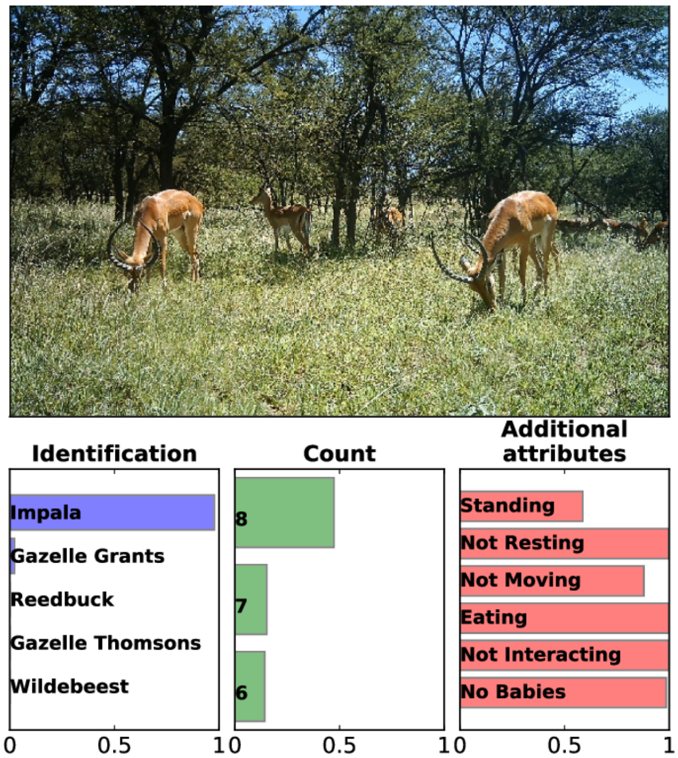

Fig. 2. Exemple of Deep Neural Networks (DNNs) can successfully identify, count, and describe animals in camera-trap images.

Apart from camera traps, AI is also changing monitoring of marine ecosystems with automatic species identification from diverse platforms such as moored observatories, AUVs and satellite imagery [22]. Deep learning models allow automated classification of marine species using a variety of information sources such as citizen science observations, benthic photo quadrats, cabled video observatories and acoustic sensors [22-24]. For instance, with acoustic data, 98.69% is achieved by CNN-based systems to recognize animal calls since marine mammal calls recorded from the sea from acoustic data instead of using a traditional method [25].

AI and species monitoring have been used for whale detection from satellite images [26], automated community ecology of planktonic foraminifera [27], as well as conservation-oriented platforms that identify animals, humans and poaching activities [28]. In particular, AI approaches have been found to be useful in predicting species interactions by trait-matching, with better performance of ML models as compared to statistical models in capturing complex ecological interactions [29].

AI and participation is is emerging direction, with some projects that use citizen science data to train AI for automatic species identification [30]. They have been described as democratizing advanced ecological monitoring through open source, low-cost, and low-powered developments [30][31] that facilitate communities' participation in biodiversity research.

With ongoing development of these capabilities, it is hoped that they will revolutionise ecological and conservation research by making analysis of large data sets more efficient, offering real time species identification, as a tool for education and by providing data which will be valuable in conservation planning and policy development [32]. Importance of these advances for science The sleeve is in the flexibility of being able to use advances like these to scale up biodiversity monitoring to levels never before seen and at a level of information that may be crucial for conservation in the inevitable face of rapid global environmental change [33][34].

B. Ai-Powered Species Distribution Models and Habitat Suitability Analysis

The use of Species Distribution Models (SDMs) has become popular in the field of ecology, biogeography and conservation biology to understand relationships between environmental predictors and species distribution. In the last twenty years, this field has embraced more and more machine learning features leading to a series of incremental model improvements [35]. Such AI-augmented SDMs can be used to model ecological niches and to predict suitable habitats more accurately as compared to classical statistical techniques, although there is a considerable variation among performance of the methodologies with respect to different ecological parameters, with predictions for presence–absence (53%) performing better than predictions of abundance, population fitness, and genetic diversity [36].

AI methodologies, including neural networks as well as ensemble learning, have substantially enhanced the accuracy of SDMs by revealing intricate associations among species and their environments [36]. MaxEnt, a popular machine learning approach to the modeling of species distributions when data are only present, has in different settings impressed with its performance with a 74.7% success rate at predicting the presence of disease-carrying mosquitos in the study of [36] Figure3. These advanced modelling approaches have employed tools like deep neural networks, GIS and CNN to predict potential habitats under existing and future environmental conditions [37].

The coupling of machine learning approaches and remote sensing has proved especially useful in habitat mapping and monitoring. These two tools offer major benefits to conservation practitioners allowing informed decisions to be made and targeted interventions to be taken to conserve threatened species and habitats [38]. For instance, spatial researchers have applied GIS and machine learning to understand the effect of urbanization on bobcat habitats in San Jose,CA by creating an original Habitat Suitability Model (HSM) that combines several environmental aspects to pinpoint critical conservation areas [39]. Similarly, in Leipzig, Germany, data from high-resolution Earth Observation and machine learning was employed to model hotspots of 44 bird species achieving 59-90% accuracy, and halting species richness of urban birds [39].

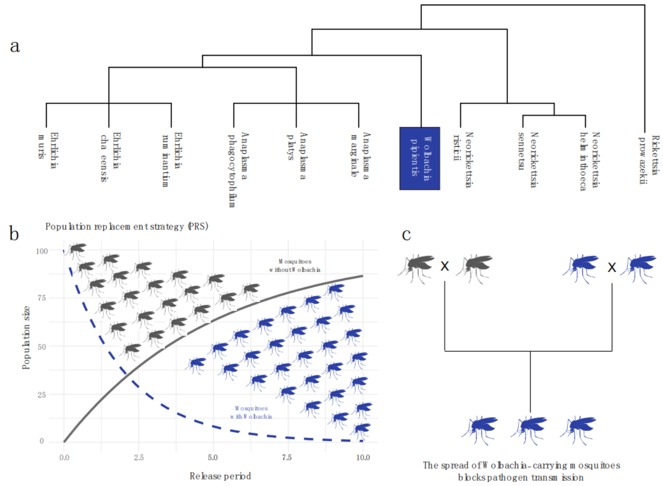

Fig. 3. Wolbachia-based population replacement strategy for mosquito-borne disease control.

Despite these developments, SDMs should be regarded as hypotheses that require testing with independent data, particularly in relation to conservation planning [36][40]. As a first step in overcoming interpretability problems associated with complex models, a new subfield known as explainable AI (xAI) provides a hope for improved understanding and interpretation of SDMs [35].

The conservation utility of AI-SDM/HSM is extensive. These technologies can process ecological data to identify hotspots of biodiversity point at risk of extinction and decide conservation priorities [41]. By participating in efforts to save endangered species, conserve biodiversity, and restore degraded habitats, AI is increasingly proving to be an essential tool in the conservation toolbox, enabling scientists and practitioners to tackle these types of complex ecological challenges in the face of a rapidly changing world.

To assist conservation practitioners in selecting appropriate AI techniques, we compare different models based on their accuracy and resource requirements. Table 2 Comparative performance and resource demand of selected AI models in ecological modeling.

This comparison illustrates the trade-offs between model complexity, interpretability, and operational costs, which are key to real-world adoption in conservation contexts.

C. Data Collection and Processing Methods for Ecological Research

Contemporary ecological study is more and more dominated by new ways of capturing and treating data fueled by A.I. These methods have revolutionized the way ecologists collect and interpret population level data:

DCNNs favor automatic analyses of images in ecology with an automatic detection of a high number of cells allowing, for example, quantitative wood anatomical investigations and accounting for the biological feature variance that needs manual handling in the past [42].

Audio Analysis and Classification methods leverage machine learning for the processing and classification of sounds

TABLE II. Comparative Performance and Resource Demand of Selected AI Models in Ecological Modeling

Model	Accuracy Range	Training Time	Hardware Requirements	Interpretability
MaxEnt	60–80%	Low	Standard PC	High
Random Forest	70–90%	Medium	Standard PC	Medium
CNN	80–98%	High	GPU	Low
DNN + xAI	85–95%	High	GPU/TPU	Medium to High

characteristic of wildlife, such as amphibian calls. These solutions use digital speech algorithms and filtering analysis to identify species according to their acoustic signatures [43] Figure4.

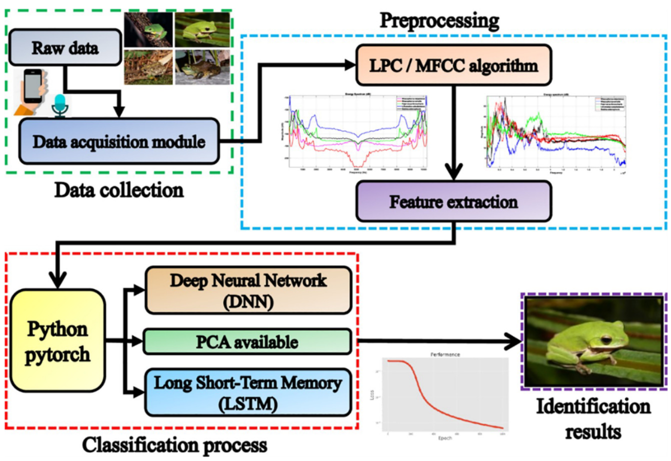

Fig. 4. The Structure of the experimental process for anuran bioacoustic classification.

Camera Trap Image Processing utilizes deep learning techniques to help sift through the millions of images and automatically identify wildlife. Such systems are capable to process around 2,000 images per minute on standard hardware, and they attain accuracy equal or greater than 98% in species classification [44][20].

Acoustic Monitoring Systems have employed convolutional neural networks for the detection and classification of echolocation calls produced by bats and other animals, with the latter being important for the processing of recordings collected in noisy field environments [44][45].

Integration of Remote Sensing and GIS: Remote Sensing and GIS Integration utilizes artificial intelligence, remote sensing imagery and GIS data to assess biodiversity at the landscape level. This integration supports generation of habitat maps, detection of ecological change, and identification of conservation priorities [46].

Plant Functional Trait Mapping applies deep learning models to field data or even photographs to map plant traits across landscapes. Recent development encompassmodels integrating field data with spectral information, and even use citizen science to map plant functional diversity [47-49].

(Field-deployed) Autonomous Environmental Sensors with embedded AI processing can process video imagery or acoustic streams on-site to identify and classify organisms to species level without external intrusion [50].

The use of deep learning in Earth Observation Data Processing permits higher resolution habitat classification, which is a prerequisite for the generation of fine-grained distributions of species across large spatial and temporal extents. Recent studies have been able to map global canopy height at 10m resolution using LiDAR data from satellite [50][51] Figure5.

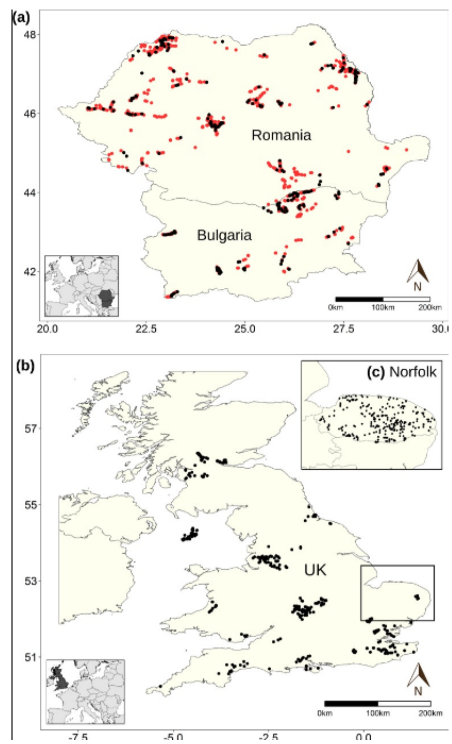

Fig. 5. Spatial distribution of the BatDetect CNNs training and testing datasets.

Multi-spectral Imaging Flow Cytometry combined with deep learning for rapid pollen identification and enumeration with high accuracy (96% species average accuracy), and morphology characterization (size, symmetry, and structure) [52].

Together these advancements have dramatically changed how ecological data are gathered and processed and, in the process, have allowed researchers to analyse extremely large datasets at scales unattainable through other measures, deriving significant patterns that would be unrecoverable by traditional means [7] [53]. The following table2 prensent differnt use cases of data collection and processing methods powered by artificial intelligence.

D. Conservation and Biodiversity Management Applications

Artificial Intelligence (AI) has become a very powerful force in the discipline of Conservation Biology and biodiver-

TABLE III. SUMMARY OF STUDIES APPLYING AI IN BIODIVERSITY MONITORING AND ECOLOGICAL PREDICTION

Papers	Data Collection Method	AI Technique Used	Ecological Application	Species or Habitat Focus	Data Processing Approach	Model Performance Evaluation
[42]	Images from transversal wood anatomical sections, manual cell area outputs	DCNN, Mask-RCNN	Quantitative wood anatomical analyses	Alnus glutinosa, Fagus sylvatica, Quercus petraea, and four conifer species	Mask-RCNN for image segmentation, compared with U-Net and ROXAS	Compared with U-Net and ROXAS; evaluated cell detection and pixel accuracy
[43]	Data collected from 32 frog and 3 toad species using bioacoustic recordings	DNN and LSTM	Species identification and biodiversity monitoring through amphibian sound classification	35 amphibian species in Taiwan, including frogs and toads	LPC, MFCC for filtering; PCA for dimensional reduction	Accuracy, training time, and comparison of DNN and LSTM with PCA
[20]	Camera traps used to collect wildlife images from five US states	CNN, ResNet-18	Classifying wildlife species from camera trap images	Wildlife in US, ungulates in Canada, Tanzania's faunal community	CNN (ResNet-18), R package MLWIC	98% accuracy in U.S., 82% in Canada, 94% detection in Tanzania
[45]	Citizen science, ultrasonic audio from road transects, iBats programme	CNN	Biodiversity monitoring through automatic detection of bat echolocation calls	Echolocating bats in Romania and Bulgaria	CNN (CNN FULL, CNN FAST) for detecting ultrasonic bat calls	Higher precision and recall in detecting search-phase echolocation calls
[33]	Continent-wide database, machine-phenotyped populations, weather, soil, satellite data	Ensemble of ML models	Crop yield prediction and understanding agronomic traits	Ten major crop species across a continent	Ensemble ML using weather, soil, and satellite data	R^2 prediction accuracy exceeding 0.8
[49]	Photos from citizen science (iNaturalist) and trait observations (TRY database)	CNN ensembles	Automated assessment of plant functional diversity through trait prediction	Plants; across growth forms, taxa, and global biomes	CNN, CNN ensembles, trait plasticity, climate factors	Accuracy enhanced using CNN ensembles and prior knowledge on trait plasticity

sity management, where many new innovative solutions are applied to complex environmental problems. Artificial Intelligence (AI) algorithms are revolutionizing wildlife surveillance by scanning through camera trap footage, while droids send back pictures of poachers from the air, analyzing the imagery and GPS data to recognize species and provide estimates of their abundance risking extinction, depending on humans´ decisions and AI algorithms scanning camera traps [54] Figure6. These technologies allow conservation biologists analyze huge amounts of ecological data, which would be infeasible to process manually, in an automated way, extensively improving the assessment of habitat health and the monitoring of populations [55].

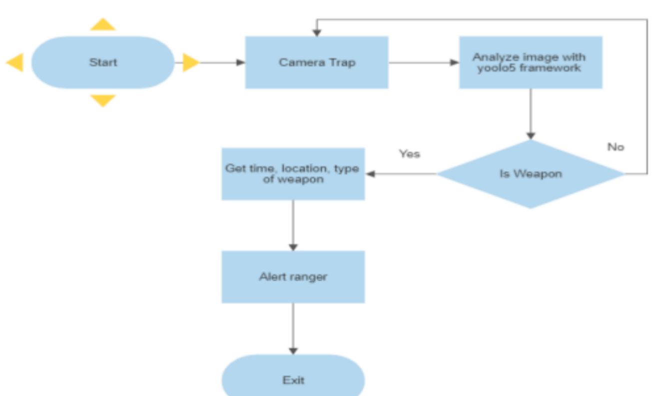

Fig. 6. Flowchart explaining methodolgy of anti-poaching system (Kuruppu, 2023).

AI combined with remote sensing instruments is seen to be particularly useful in habitat evaluation and resource preservation. Machine learning models with satellite imagery to identify forest cover changes, deforestation patterns and areas in need of environmental restoration can be used for this purpose [55]. This combination provides dense spatial and temporal information for otherwise poorly studied areas, with the analyses showing that even common methods like RF and GLM can predict relatively well different metrics of biodiversity [56][57] Figure7.

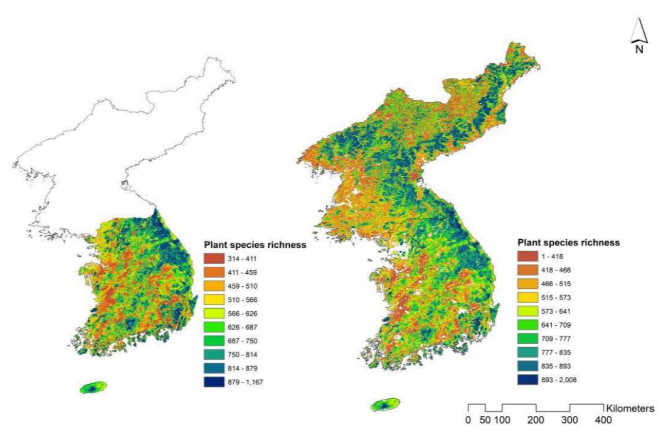

Fig. 7. Potential plant species richness estimated from S-SDMs in South Korea (Left) and estimated by th deep learning model in the Kor an Pe insula (Right).

AI's capability to handle multiple types of data, including acoustic recordings, eDNA, and imagery for species identification, to estimate biodiversity levels, and to identify new or threatened species has revolutionized biodiversity monitoring ([54]). Machine learning-type algorithms can monitor changes in population dynamics and evaluate the response of biodiversity to changes in the environment, which is important to design conservation programs and to determine how loss of biodiversity will impact ecosystem function [58].

Arguably most importantly, predictive modeling enabled by AI can inform effective proactive conservation efforts by predicting the impacts of interventions on environmental changes and the dynamics of animal populations [55]. By combining historical and contemporary measures of decline or rate of increase of numbers of certain species and incorporating environmental change into the models, they can be used to predict potential future threatened species, thereby providing early warning of invasive species imbalance in ecosystems [59]. The ability to construct predictive models at these vast scales has the potential to transform ecology and environmental sciences in the way that statistics did over the course of the twentieth century.

AI is also improving conservation through integration of data and support of decision making. AI-supported analytics help to integrate various sources of data and present insights to support evidence-based decisions for conservation [55]. Methodological learning from comparative exercises with AI models such as ours is one way to support the development of stronger and generalisable solutions to biodiversity and habitat management [60]. Apart from direct conservation applications, machine learning also add value to conservation learning and education through the analysis of complex ecosystem data, such as climate data, soil property, and human action [59].

With overlaid environmental issues of climate change, loss of biodiversity, and zoonotic disease spread and how they intertwine the solutions, AI may provide useful tools to address such complexity [61]. AI technologies are increasingly indispensable tools within the context of modern conservation, as they allow us to automate monitoring of wildlife, improve habitat assessment, conduct advanced analyses of biodiversity, and build predictive models of species' distributions.

In a successful real-world application, a deep learning system deployed in Tanzania's Serengeti region processed over one million camera trap images to identify mammal species with 94% accuracy, significantly reducing manual labor for field researchers [20]. Similarly, AI-enhanced drones have been used in South Asia to detect and deter illegal poaching activities by combining object detection with real-time GPS alerts [28]. These examples illustrate the practical benefits and impact of AI-powered conservation tools.

E. Limitation and Future Directions

Although AI has greatly reshaped ecological and in particular biodiversity research, there are still major incomplete of AI approach and some challenging. The primary challenge is the data dependency of machine learning methods that need long high-quality well-balanced datasets that are rarely available in ecosystem contexts. This is especially problematic for the rarer species or the less studied ecosystems, as the data scarcity might result in model bias or low generalization. In addition, most ecological data sets are subject to biases introduced by selective sampling, taxonomic preferences, and geographic imbalances that may be amplified by AI models and result in erroneous conclusions.

There is also one important challenge to remain unanswered: "black box" property that belongs to many popular deep learning methods, because complex models are often "opaque" to a variety how they make the prediction by themselves and solvers, and it is hard for ecologists to interpret how those identified patterns may be relevant to the ecological process. This interpretability issue has driven the need for explainable AI (xAI) models that are able to offer explanations over decision making while retaining the skills of prediction.

From a practical point of view computational prerequisites are still, in most cases, out of reach of most performing (not computer scientists) research groups in ecology, since the "standard" training of complex neural networks requires special hardware and, in some cases, specific technical know-how, that it is not going to be part of the one found in a normal ecology department. Such a technical hurdle not only restricts wider access, but also may amplify the existing disparities in the availability of research capacity.

More fundamentally, there is a gulf between statistical prediction and ecological understanding. Although AI can learn patterns exceptionally well, as AI it may not advance ecological theory or mechanistic understanding in the absence of domain integration. It's part and parcel of the machine-learning world." Critics, however, point out that machine learning models can prioritize prediction at the cost of explanation, raising questions about their scientific value.

In the future, there are several promising avenues to tackle these issues. First among these is the emergence of easier-to-use tools and platforms that greatly lower the technical barriers to entry to AI-based ecological research. Projects like Wildlife Insights and iNaturalist show that user-friendly interfaces can democratize the use of powerful AI tools.

Transfer learning and few-shot learning methods are promising for addressing the constraint of few data by transferring models trained on data-rich species to closely related yet data-poor species. Such methods could potentially be used to transfer AI benefits to poorly studied taxonomic groups or ecosystems.

Reinforcing the interface between ecologists, computer scientists and statisticians is another important way forward, which should lead to better consideration of the ecology when designing AI tools, instead of just running a generic algorithm on ecological data. This partnership is particularly relevant for hybrid model development where the complementary strengths of machine learning, predictive performance, and mechanistic models, theoretical and interpretability related, need to be integrated.

The future for AI in ecology may involve the development of frameworks that combine multiple AI approaches with domain knowledge to satisfy both predictive needs and mechanistic understanding. For application purposes, however, it is desirable that researchers can interpret models within theoretical frameworks other than the one in which they were developed, by borrowing strengths from alternative modeling paradigms. With climate change intensifying and biodiversity decline proceeding, such integrated methodologies will be paramount to achieving effective conservation management informed bydata-driven knowledge and ecological understanding.

To mitigate geographic and taxonomic biases in training datasets, several strategies have been proposed. These include transfer learning, where models trained on data-rich species are adapted to underrepresented taxa, and the use of synthetic data generation to augment sparse datasets.

Explainable AI (xAI) can address the black-box limitation of deep learning models. For example, SHAP (SHapley Additive exPlanations) values allow researchers to identify which environmental variables most influence a model's prediction of species presence, enhancing trust and transparency for ecologists and decision-makers alike.

V. Key Takeaways

• Neural networks enhance prediction of habitat suitability across ecosystems,

• Models like MaxEnt remain relevant due to simplicity and transparency,

• xAI offers promising solutions to bridge interpretability gaps,

• Resource needs vary widely; GPU-based models may limit accessibility.

VI. Conclusion

The augmentation of artificial intelligence with ecology research represents a state-of-the-art tool in the study, monitoring, and protection of biodiversity. In this systematic review, we have aggregated almost thirty years of worldwide research that applies AI (in particular ML and DL) to species preference analyses, ecological niche modelling and conservation recommendations.

Our review, therefore, underscores a dynamic, cross-disciplinary field that has grown exponentially since 2015 due to rapid technological development, enhanced ecological importance, and the increase in big environmental data. There are applications ranging from automated species identification in terrestrial and marine environments to sophisticated habitat suitability modelling and decision support systems. Thanks to machine learning and artificial intelligence, researchers today are able to keep track of what is happening to biodiversity across space and time at a faster and truer pace than ever before, turning static ecological censuses into dynamic feedback loops.

However, there is still much more to be done. Ecological data-sets are frequently incomplete, imbalanced or biased towards certain geographies –attributes that may limit the accuracy and generalization of predictive models. In addition, the black-box nature of a lot of AI systems is an issue for interpretability, transparency, and trust, especially in conservation where decision making has real worlds ecological and ethical consequences. There is greater urgency for explainable AI (xAI), for more equitable access to computational resources, and for more interdisciplinarity.

In the context of habitat intelligence, the future will involve hybrid frameworks that combine the predictive power of AI with mechanistic ecological theory. Recent developments including transfer learning, citizen science linkage, and low-cost sensing are leading to an increasing degree of involvement and translation, especially in underrepresented geographies and ecosystems. By fostering collaboration among ecologists, data scientists, and decision-makers, the community can develop scalable, interpretable and actionable tools that address the twin crises of climate warming and biodiversity loss.

Together, they illustrate that AI has the potential to truly revolutionize ecological science as an exciting complement to its traditional iteration, not a replacement. By exposing previously hidden patterns in species–environment interactions, AI supports better, faster and more strategic conservation action. While this area is still emerging, it is clear that it will be fundamental in the future of biodiversity and the management of life on the planet.

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