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Methods

Challenges and opportunities for Artificial Intelligence for predicting changes in ecological communities

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Abstract

Ecology should be capable of convincingly demonstrating the consequences of changes in advance to become the strong predictive science that it needs to be. Predictive ecology could greatly assist conservation policy-makers by enabling them to understand and assess alternative management scenarios.

Predicting changes in ecological communities require complex models and large empirical datasets. Deep Learning (DL), in combination with Organism-based Ecology (OE), could be used to construct models capable of predicting how organisms interact with each other and with their environment and how these interactions drive community change.

At present, traditional ecological data are insufficient to train such models. A completely new type of data is needed, data that captures the information organisms use to guide their actions and responses to changes within their communities. To address this, we propose developing sensory instruments that simulate organisms' sensory organs to collect these data.

We also call for the explicit study and publication of the limits of applicability of DL models and we propose establishing a set of ethically responsible rules for applying DL models in ecology.

Key words: Deep Learning, individual-based, information processing, organism-based, predicting communities, sensory instruments, training data

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Introduction

Since the international Convention on Biological Diversity in Rio de Janeiro in 1992, countries have been striving to halt the decline of biodiversity (GBO 5 2020; WWF 2024). Different approaches of nature conservation have been applied, varying from *ex situ* raising of species at the edge of extinction in the wild to strictly fencing off large wilderness areas from human activities and rewilding presently disturbed areas. In many cases, nature conservation has been successful, in others unsuccessful and in yet other cases, the impact has still to be established (Simkins et al. 2025; Tobias et al. 2025). Common practice in nature conservation is that, based on ecological reasoning and experience, measures are taken and then evaluated after some time. However, evaluation can be difficult when the objectives of the measure and/or the period over which

changes can be expected are unclear. This lack of clarity seems often true for the impact of measures on ecological processes or communities (Tobias et al. 2025). Who could have predicted that the re-introduction of the grey wolf (*Canis lupus*) in the Yellowstone National Park would even change the course of the river (Smith and Peterson 2021; Ripple et al. 2025)?

We believe that ecology should be capable of convincingly demonstrating the consequences of changes in advance in order to become the strong predictive science that is needed (Peters 1991). Accurate predictions of the future state of communities would enable us to show the consequences of changes, such as increasing the area of nature reserves, reducing the physical isolation of reserves, limiting fertiliser emissions, halting water withdrawal, re-introducing large herbivores or predators, controlling invasive species or increasing freedom of organisms (De Snoo and Musters 2025). Moreover, it would substantially support conservation policy and provide clear information on how to evaluate nature conservation measures. It would also enable conservation policy-makers to study alternative management scenarios and it would give trustworthy explanations of management decisions to the public (Mouquet et al. 2015; De Koning et al. 2023; Zurell et al. 2025).

The inability of ecology to accurately predict how communities respond to change has often been asserted (Peters 1991; Lawton 1999; Mouquet et al. 2015; Elliott-Graves 2019; McIntire et al. 2022; Musters et al. 2023; Jeltsch et al. 2025; Williams and Pettorelli 2025; Catford et al. 2026). Ecological communities are usually very complex, including many biotic actors under various abiotic circumstances that result in numerous processes, including negative and positive feedback. Many of these processes are well studied and successfully described in mathematical models (Begon et al. 2006; Vellend 2016). However, bringing these models together into a General Ecological Model (GEM) for communities has as yet only been partly successful (Töpper et al. 2025). It seems that the simplifications that are needed for model building, such as the use of emergent features of groups of actors or processes, may miss essential features of a community, for example, its overwhelming contingency to local biotic and abiotic circumstances (Lawton 1999). Moreover, a fundamental challenge in predicting communities is the chaotic behaviour that some populations may show. Chaotic behaviour occurs when unnoticeable small differences in the starting conditions of a population lead to large differences in the long-term outcome. Chaotic behaviour of populations may lead to chaotic behaviour of state variables of locations, a phenomenon not uncommon in nature that can cause a loss of predictive accuracy over time (Rogers et al. 2022). This means that, even with sophisticated models, it is uncertain whether predictions of community changes will be accurate for the timescales relevant to policy-makers.

Lawton (1999) argued that the overwhelming contingency is true for communities at the 'intermediate' scale, but may not be true for the small, such as populations of single species or large scale, such as the biomes of earth. However, for nature conservation, the intermediate scale is probably the most relevant one. Of course, the 'relevant' scale depends on the window through which we are looking at nature (O'Neill et al. 1986; Klinges et al. 2026). Additionally, since the need for nature conservation is motivated by our human concern with the decline of biodiversity, the human perspective seems to be relevant. We can assume here that the relevant scales from the human perspective cover spaces of ca. 1 to 1,000,000 km^2 and time periods of ca. 10 to 100 years. The spatial extent

of nature conservation is limited by management scales. The largest protected terrestrial area being almost 1 million km^2, while the largest protected sea area is almost 2 million km^2 (https://en.wikipedia.org/wiki/List_of_largest_protected_areas). Predictions over less than 10 years seem irrelevant because the accurate prediction would, in most cases, be that the community is almost the same as it is now and irrelevant over more than 100 years because it would become pure science fiction in view of the fast changes of human technology and the large impact that these may have on the environment. The following is written with an area of ca. 10 km^2 over ca. 25 years in mind. It is unclear whether chaotic behaviour of communities can be expected at this time scale, although it has been shown that small taxa with short generation time have a higher chance of showing chaotic behaviour than large taxa with long generation times (Rogers et al. 2022).

To address the difficulty of predicting communities for nature conservation, several authors have proposed a new ecological framework, based on the actions of ecological agents, specifically individual organisms (DeAngelis and Mooij 2005; Grimm and Railsback 2005; Purves et al. 2013; DeAngelis and Diaz 2019; Gouveia et al. 2020; Musters et al. 2023; Grimm et al. 2025; Jeltsch et al. 2025; Musters and De Snoo 2025; Gold et al. 2026). This Organism-based Ecology (OE) can be defined as ecology that takes the individual organisms as the entity whose actions cause the recurring patterns that can be observed within and amongst communities (Gouveia et al. 2020; Musters et al. 2023; Jeltsch et al. 2025). It differs from traditional ecology that it does not *a priori* assume that actions of organisms can be summarised in actions of species. It defines communities as networks of organisms. However, this means that communities at intermediate scales are even more complex, including many more entities and interactions, the nodes and edges of networks, than in the traditional species-based approach. The interactions arise from the actions of individual organisms (Kauffman 2019; Ball 2023; Musters et al. 2023; Musters and De Snoo 2025). To survive and reproduce, organisms constantly and autonomously respond to the community and environment in which they are living (DeAngelis and Diaz 2019; Ball 2023; Mitchell 2023; Sayin et al. 2025). For that, they rely on information from both within their bodies and from their biotic and abiotic surroundings. Internal information is stored in their genes and is also present in current metabolic states and in the memory of past experiences. It helps organisms, together with information from the environment, to react adequately to changes within the community and their surroundings. External information is gathered through all kinds of sensory organs or organelles, a process common to all types of organisms, whether animals, plants, fungi or microbes. Thus, the processes in ecological communities not only involve the processing of energy and materials by organisms, as emphasised in traditional ecology through concepts like carrying capacity and food webs, but also by the processing of information by organisms. This information is not only present in the abiotic surroundings of the organism, but also in the signals that other organisms cause.

Therefore, OE probably requires extremely complex models for being able to predict changes in communities (Purves et al. 2013; Musters and De Snoo 2025; Gold et al. 2026). It has been suggested to use Artificial Intelligence (AI) for constructing these models (An et al. 2021; Jeltsch et al. 2025; Musters and De Snoo 2025). To our knowledge, such models are not yet available (Reynolds et al. 2025). However, the results of simulating fly behaviour in the Eon

project (https://eon.systems/updates/embodied-brain-emulation) shows that digital simulating of an organism's behaviour can be done, while Park et al. (2023) show that AI-models are able to simulate realistic interaction behaviour between generated agents, in this case proxies of human beings.

To increase predictability, two fundamental approaches can be recognised (Alexandrov 2025). The empirical-based approach starts with identifying patterns in empirical data and then tries to formulate theories or hypotheses that can predict these patterns. The process-based starts with building models based on theories or hypotheses of processes and tests the predicted patterns of these models in empirical data. In good science, these two approaches are supposed to alternate, thus stepwise increasing the body of empirical knowledge (Platt 1964; McIntire et al. 2022).

The call for OE was inspired by the success of Individual-based or Agent-based Modelling (Grimm and Railsback 2005; Musters et al. 2023; Gold et al. 2026). However, an empirical-based approach of OE is still lacking, except in some studies of trees (e.g. Liu et al. (2016)). AI (and, especially, Deep Learning (DL)), is fit for identifying recurring patterns in empirical data and it has shown to be able to generate the same patterns in fields like text processing, music, movies and weather forecasting. Therefore, DL appears to offer a promising solution for solving at least part of the prediction problem in ecology: it can identify patterns in complex ecological data and may be able to predict changes in these patterns (Christin et al. 2019; Musters and De Snoo 2024; Cipriano et al. 2025; Frazier and Song 2025; Musters and De Snoo 2025).

In our search for models that can predict the state of ecological communities, we define the state of a community as the spatial distribution of organisms at a certain moment in time. From that, a spatial and temporal description of a community in any set of ecological variables becomes possible, that reflect this distribution of organisms across an area at a given moment and track changes therein over time. Examples are variables such as change in distribution of biomass, species richness, abundance, genetic diversity, functional diversity or resilience. This is similar to how meteorological models predict weather patterns, such as change in temperature, rainfall, wind direction and atmospheric pressure, for a given location.

Various suggestions exist for the set of ecological variables to use, such as Ecological Integrity, Essential Biodiversity Variables and Ecosystem Coupling (Pimentel et al. 2000; Pereira et al. 2013; Ochoa-Hueso et al. 2021). However, this is not the place to discuss these options in detail. For an overview, see Burgess et al. (2024).

In this paper, we aim to explore whether DL models could be suitable for predicting changes in ecological communities. We will begin by discussing some of the theoretical prospects and limitations of DL models. Next, we will focus on the types of data needed to train these models effectively. Finally, we will address the risks of applying DL when data are insufficient.

Prospects and present limitations of DL for predicting communities in ecology

We follow the taxonomy proposed by Pichler and Hartig (2023), who define AI as a broad category of techniques that use algorithms to achieve human-like performance in specific decision-making or recognition tasks. For more

extensive discussions of AI in ecology, see Christin et al. (2019), Borowiec et al. (2022), Pichler and Hartig (2023), Han et al. (2023), Sandbrook (2024), Alexandrov (2025), Bogoni et al. (2025), Cipriano et al. (2025), Frazier and Song (2025), Rafiq et al. (2025) and Reynolds et al. (2025). Machine Learning (ML) serves as a key tool in AI systems, enabling them to learn from data and make predictions based on new information. Deep Learning (DL) is a subfield of ML (Cipriano et al. 2025). It refers to learning by algorithms having an architecture inspired by human brains, i.e. neural networks. Calculations are performed in layers. Neural networks learn complex patterns and hierarchies in large datasets through forward and backward propagation of preliminary results between layers, adjusting weights to minimise prediction errors. They can have multiple hidden layers. DL may be especially useful in predicting changes in ecological communities because of its ability to handle large and heterogeneous datasets and quickly perform complex tasks like image recognition, acoustic processing, time-series analysis and landscape structural modelling (Pichler and Hartig 2023; Cipriano et al. 2025; Frazier and Song 2025).

All the above cited articles reviewing the use of AI in ecology discuss the problems of AI application extensively. We will concentrate our discussion on the prospects of DL for predicting communities, wrong predictions, lack of clarity of how DL comes to its predictions and wrong applications of predictions. Although the environmental issues related to the applications of DL, such as the costs and risks of materials, energy and human resources uses, are very important and, in themselves, reasons not to apply DL, we refer to Sandbrook (2024) for an extensive discussion.

Prospect of DL for predicting communities

As we described above, communities change not only because (a)biotic processes alter the availability of material and energy for organisms, but also because organisms process information. This means that they change in reaction to the biotic signals they perceive from their surroundings, which also changes the way they interact. Therefore, a DL model is needed that is fit for predicting changes over time, based on data on material, energy and biotic signals. The family of DL algorithms best suited for this task are Recurrent Neural Networks (RNNs; Christin et al. (2019); Pichler and Hartig (2023)). RNNs are trained using time-series data. The model predicts the state of a community at each time step and adjusts its parameters to minimise the difference between the predicted and actual states. The model is then used to predict the next time step and so on. To accurately predict changes in the state of communities, i.e. the spatial distribution of organisms, models should be trained with data on the spatial distribution of organisms, material, energy and biotic signals present within a community and the changes therein (Fig. 1). Many process models that accurately and efficiently describe abiotic processes, as well as the reactions and interactions of individual organisms, are already available (Grimm and Railsback 2005; Purves et al. 2013; Gold et al. 2026). Although these models could be incorporated into a workflow that includes DL models, care should be taken to avoid introducing biases (see the next section). Large Language Models (LLMs) appear to be well-suited to combine the heterogeneous data and outcomes of different model types in an accessible way, providing a complete prediction workflow (Reynolds et al. 2025).

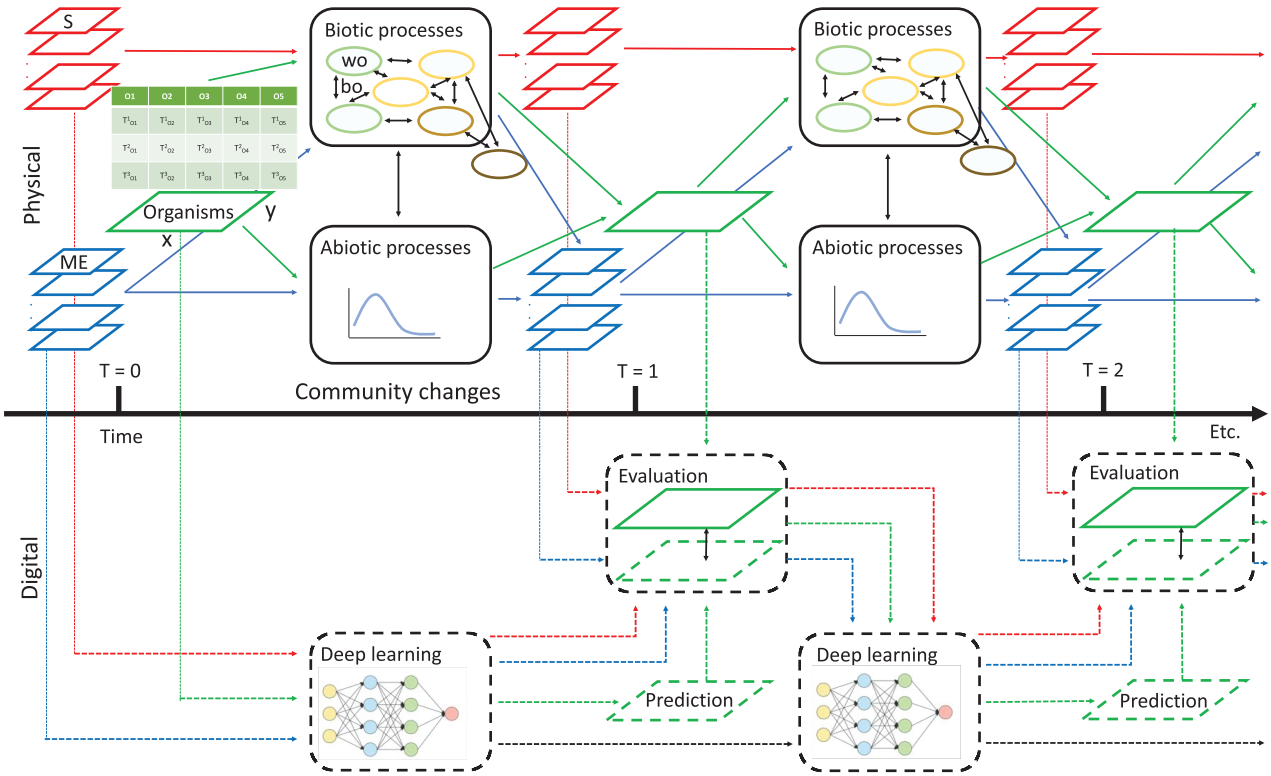

Figure 1. Flow diagram of the first three time-steps of a Recurrent Neural Network to predict changes in the state of community. The state of the community is defined as the spatial distribution of organisms and includes each time step information on the traits of each organism (only shown here at time = 0). The above part of the diagram represents the physical community as a set of spatial characteristics of the community at a given moment in time. These characteristics change because of biotic and abiotic processes (wo: biotic processes within organisms; bo: biotic processes between organisms). Red is the distribution of biotic signals (S), blue that of material and energy (ME) and green that of the organisms. The lower part of the diagram is the digital representation of the community (broken lines), including the prediction of the distribution of organisms. Evaluation not only includes the distribution of organisms, but also that of signals, material and energy.

However, it is obvious that modelling every single organism and every interaction would lead to a tremendously large and complicated model system, involving huge computational time and costs, even in case of a small community. Simplification is undoubtedly needed, certainly for exploring the prospects of the development of a DL modelling pipeline. One form of simplification is grouping organisms together and using emergent features of these groups for modelling. Operational Ecological Units (OEUs) have been proposed for that (Musters et al. 2023). Process models could be used to estimate the emergent features, including variance within them. The same can be applied for groups of interactions, abiotic processes and even scales (Gold et al. 2026).

Wrong predictions

A key challenge with DL models is the potential for generating non-realistic results. First, DL need large and high-quality datasets for training. We will discuss this issue further in a separate section, because DL for ecology becomes DL for OE by training them with the appropriate data, that is, data of organisms. Second, algorithms may explore solution spaces that include physically, chemically or ecologically impossible scenarios. For example, they might predict closed systems that do not conserve mass and energy or population

sizes that become negative. In ecological contexts, some combinations of variable values may be implausible, such as high predator biomass combined with low prey biomass, even though the outcome of each individual variable might be valid. Therefore, to prevent unrealistic predictions, constraints must be built in (Pichler and Hartig 2023). Additionally, integrating well-established sub-models, such as physical laws, the Madingley model (Töpper et al. 2025), process-based models (Alexandrov 2025) and agent-based models, including energetic models (Grimm and Railsback 2005; Gold et al. 2026), into the DL models can help to maintain ecological plausibility. However, it should be realised that these latter models may be biased towards current ecological views on the importance of specific processes, such as resource use, metabolism or competition, in shaping community dynamics.

How does DL come to its predictions?

A well-known problem of DL is that, although the predictions of a DL model may be accurate given the data, it remains unclear how the predictions are exactly generated because of the complexity of the models using hidden layers and a combination of different techniques; DLs are black boxes (Cipriano et al. 2025). This has been called the lack of transparency of DL. It is not only a problem for convincing stakeholders of the relevance of the predictions of DL models (Pichler and Hartig 2023), but also a problem in using DL in the above-described circle of good science where empirical-based and process-based approaches alternate. Explainable AI (xAI) is a field where techniques are developed to better understand the results of DL (Pichler and Hartig 2023; Frazier and Song 2025). At some point in the future, it might even become possible to ask LLMs to suggest models that are able to predict the same results as the DL-models and that are based on process-based approaches. However, in the end, DL predictions should always be checked for causal interference and these causal interferences should be used for giving the predictions theoretical substantiation that can be tested thoroughly (Mouquet et al. 2015). DL thus becomes a hypothesis-generating technique. Ultimately, this approach may offer valuable insights into the relative importance of different mechanisms in community ecology, advancing our understanding of ecological processes and contributing to the development of General Ecosystem Models (GEMs) and Digital Twins (DTs) (Purves et al. 2013; De Koning et al. 2023; Trantas et al. 2023; Frazier and Song 2025). This approach should also reduce the computation time and costs of models that predict changes in communities.

Wrong applications of predictions

Since AI models are empirical based by nature, the well-established principle of not extrapolating empirical findings beyond the scope of the dataset should be respected in case of DL models as well. For example, when a behaviour model for individual Blacktailed Godwits (*Limosa limosa*) is trained with data from western Europe, all individuals would be predators collecting soil invertebrates. However, applying such a model to the birds at their winter habitats in western Africa would be a mistake, because there, the same

birds become omnivores, mainly feeding on rice (Cramp and Simmons 1983). However, due to the lack of transparency, it may be difficult to assess when the model's application is justified or when it is not (Borowiec et al. 2022; Cipriano et al. 2025). This, together with the lack of theoretical substantiation, makes generalisation of DL models problematic. For this reason, the scope of applicability should always be rigorously tested, for example, by applying the DL-model, as routine, to data not used for training, such as from a different region or period. The results should explicitly be published. A special case is unintentional colonialism (Reynolds et al. 2025). When DL algorithms are trained using data that include information about human use of natural resources, the model's predictions may inadvertently incorporate the cultural biases of the humans involved. If these models are then applied to communities in regions where local cultural views differ, the conservation actions recommended, based on these predictions, may be completely misaligned with the preferences and needs of local people. This could lead to decisions that are perceived as a form of cultural imposition or colonialism. For example, in case of the above-described Godwits, the birds are generally loved in western Europe and chosen as the national bird of the Netherlands. In western Africa, however, the same birds are regarded as a burden for farmers, because of their consumption of large amounts of rice.

However, this is not the only ethical issue concerning generating and disseminating ecological predictions (Mouquet et al. 2015). We urge ecologists to consider the development of a set of ethically responsible guidelines for applying DL models in ecology, ensuring that the cultural context of conservation decisions is always considered.

Data needed for DL training

We think that the best chance for DL models to predict the right patterns in the distribution of the organisms in future communities is through training them on data that reflect the past and present distribution, as well as the actions and reactions of ecological agents, the organisms themselves.

For that, data are needed that can be used by AI to assess the spatial distribution of the organisms within the study area at a certain moment in time. Since the focus is the change of the complete community, we should not confine ourselves *a priori* to a limited group of organisms, although presently, we are not able to assess the prevalence of all organisms in an area.

As explained in the Introduction, actions and reactions of organisms include information processing by the organisms. Therefore, for predicting future patterns in the distribution of organisms, it is crucial to include datasets that capture the information organisms use to evaluate their surroundings. This approach is a new frontier for ecological data collection. Historically, ecological data collection has rarely been focused on how organisms perceive their environment, except in cases where human-induced disturbances, such as by artificial light or noise, are assumed to affect organisms' behaviour (Halfwerk and Jerem 2021). To collect such data, ecologists will likely need to collaborate much more closely with ethologists than they have in the past (West et al. 2025). A great advantage of DL is that it can handle highly different types of data from all kinds of sources (Reynolds et al. 2025).

Traditional ecological data

Ecological communities have been studied empirically since the early 20th century (Vellend 2016). Prior to that, in the 19th century, explorers collected and catalogued species and stored them in museums worldwide (Suarez and Tsutsui 2004). Since the 1960s, when concerns about declining biodiversity emerged, systematic monitoring of natural systems has been implemented in many regions of the world (Gaiji et al. 2013). As a result, vast amounts of ecological data are available. However, these datasets have well-known limitations: they are taxonomically, spatially and temporally biased, focusing mainly on large species, western Europe and the United States and short time series collected under favourable weather conditions during the daytime (Mora et al. 2011; Gaiji et al. 2013; Vellend 2016; Díaz and Malhi 2022; Burgess et al. 2024; Díaz-Calafat et al. 2024; Ki et al. 2025; Lalechère et al. 2025; Santana et al. 2025). Additionally, much of the data, especially raw data, may not be publicly available (Listgarten 2024; Ravenscroft et al. 2025), limiting their usefulness for training DL algorithms (Santana et al. 2025). Consequently, current datasets are highly insufficient for estimating the parameters needed for general applicable predictive models, whether for GEMs (Evans et al. 2013) or DL models (Listgarten 2024; Mishra 2026).

Data for organism-based ecology

A more fundamental issue lies in the fact that most current datasets are based on traditional ecological approaches, which focus on species. However, for OE, we need data of individual organisms, which are still rare (Musters et al. 2023). The spatial distribution of organisms needs to be assessed, as well as changes in this distribution over time. For that, datasets need to recognise individual organisms. Recognition of individual organisms is still very problematic in many groups of organisms, although for some groups, such as plants, it may be easy and for others, such as birds and insects, new techniques, like recognition by images and sounds, are developing quickly. Additionally, genetic techniques for recognition of individuals may become available for collecting ecological data in the field.

As said before, for training DL-models for OE, datasets are needed that encompass the information organisms use to maximise their survival and reproduction. A possible approach is to consider the sensory organs involved in the perception of the environment to get an idea of the data that should be collected. Information related to vision, audition, micro-climate, chemical signals, pressure and electromagnetic fields could be highly relevant. Electromagnetic information, for example, has been shown to be used by various organisms (Levitt et al. 2022; Thill et al. 2024), the many volatile and non-volatile metabolics that organisms produce create a chemodiversity landscape for organisms (Hanusch et al. 2026) and the spatial structure of soils and vegetation may also play a significant role (São Pedro et al. 2025; Wagenaar et al. 2025). Furthermore, information on the community in the past or data from organisms at larger distances than the predefined location, could be important (Musters and De Snoo 2024; Klinges et al. 2026). DNA and RNA in air, water and soil (eNA) may provide relevant data on organisms not directly observable (Cook et al. 2025).

New data collection methods

Fortunately, new technologies for automatic data collection are rapidly increasing the availability of data, suitable for training DL models (e.g. De Koning et al. (2023); Ravenscroft et al. (2025)). Particularly when data collection focuses on the behaviour and sensory information of individual organisms, we think that substantial progress can be made towards developing DL algorithms that predict community change. Technologies like camera trapping and biologging are already enabling the recording of organism behaviour and are becoming more widely available (De Koning et al. 2023; Ellis-Soto et al. 2025). Moreover, we propose that new instruments should be designed to measure the same types of information as organisms' sensory organs, such as light, visual imagery, sound, volatile organic compounds, including pheromones, nutrients, pH, air and water pressure, temperature, humidity and electromagnetic fields, at the same time. However, since these instruments need to cover the sensory range of as many organisms as possible, the ranges of, for example, light and sound frequencies should be broad. Measuring a large range of chemical compounds at once seems still a great challenge, although developments in e-nose technology may be promising (Chen et al. 2022; Hanusch et al. 2026) and new fields of data collections come into view, such as the use of eco-acoustics for measuring belowground biological activity (Taylor et al. 2026). A prerequisite of these instruments would be that data-collection does not disturb the organisms and their behaviour. For that, (semi)permanent data-collection instruments can be installed at fixed locations of which the data can be read out at long distances, a technique common in use in space studies. Drones and satellites can be used for collecting geophysical data and data of the canopy.

Data processing could be automated and continuous through the use of AI, with pattern recognition techniques already well-developed for images and soundscapes (Reynolds et al. 2025). When it is possible to extend these techniques to other sensory inputs, these new instruments would be capable of identifying organisms and recording their position, traits and state in real time, as organisms do. These data could then be used for finding spatial patterns in the distribution of the organisms and the change of these patterns over time by DL. Once such sensory instruments are available, data collection and processing could take place at much lower cost than under traditional data collection.

Some of the technologies that are already available might be used to design prototypes of such instruments and apply them in small nature conservation areas for which much information is already available. The combination of traditional monitoring, satellite imagery, camera trapping, biologging and the prototypes of the new sensory instruments could deliver the data for training the first experimental DL models that try to predict changes in the chosen areas. These models should then be extensively tested, including checks of causal interference, hypothesis generation and hypothesis testing and then developed further.

A virtual research proposal could illustrate this approach. Imagine a research area of 1 km^2 of forest in which a quarter of the area is cleaned of vegetation. The question is how to predict the development of the vegetation and bird community in this area. For this, every month the following data are collected at a grid of 100 m^2: plant species coverage in a 10 m^2 area; tree growth, bloom and seed setting; one day of bird song, camera trapping of vertebrates and insects, sunshine, precipitation, temperature and wind; one set of soil samples. Plant

coverage and tree growth are used to estimate changes in total aboveground biomass of the vegetation. Bird song and camera trapping are used to assess the species, number of individuals and distribution over age, size and feeding classes of individual birds and other vertebrates. Camera trapping of insects is used to estimate changes in insect biomass over feeding and food classes. Soil samples are used to estimate changes in soil productivity. For estimations, classic ecological models are used. After five years of data collections, an RNN is trained and used for predicting the next year monthly distribution of individual trees and birds over the research area and, after that, yearly improved.

Initially, the predictions will likely be short-term, but over time, they could extend further into the future and become increasingly relevant for policy-making. Additionally, older data could be integrated into the training sets of DL algorithms to improve long-term predictions.

Risks of shortage of training data

Current training data for DL models for OE are insufficient (Mishra 2026). The risks of using predictions from models trained on unrepresentative and incomplete datasets are significant (Borowiec et al. 2022; Cipriano et al. 2025). For example, studies have shown that popular taxonomic groups of insects cannot be used to predict the conservation status of other groups (Pilière et al. 2016; Musters et al. 2024). Ellis-Soto et al. (2025) demonstrated on a global scale that biologging datasets are not representative of the environments of interest.

Models trained with incomplete data are likely to overlook critical mechanisms essential for predicting changes in ecological communities. For instance, a DL model trained only on vertebrate data would completely miss vital processes like vegetation production and the decomposition activities of invertebrates and microbes. Furthermore, as discussed earlier, present knowledge of community changes may be biased towards certain ecological processes, which can also lead to biased data collection. When such data are used for training, the resulting AI models will reflect our limited knowledge, rather than providing objective predictions.

There are algorithms designed to address the issue of insufficient training data (Christin et al. 2019; Wang et al. 2020; Andrew et al. 2025). However, we are concerned that these techniques may only mask and amplify the unrepresentativeness and incompleteness of ecological data, potentially exacerbating the risks associated with inaccurate predictions (Listgarten 2024).

Conclusions

Deep Learning (DL), in combination with Organism-based Ecology (OE), could be used to construct models that might be capable of predicting how organisms interact with each other and with their environment and how these interactions drive community change. Such models are not yet available and it is not clear that, when they become available, they will be relevant for policy-makers. What is clear, though, is that many problems must yet be overcome.

The main advantage of DL over traditional process-based models is that it relies largely on empirical data to simulate changes. If we manage to build DL pipelines that minimise our present bias in ecological knowledge, this ability to predict,

based on empirical data, could significantly enhance our understanding of ecology. In turn, this could contribute to the development of more accurate process-based models and increase the likelihood of successfully creating reliable GEMs and DTs for ecology (Purves et al. 2013; De Koning et al. 2023; Trantas et al. 2023).

However, the way forward has significant challenges. The first hurdle is selecting an appropriate set of response variables to model (Mouquet et al. 2015). We propose that DL itself could be used to help identify these variables, offering an opportunity to move beyond traditional ecology. The structure of the models should be flexible (McIntire et al. 2022), inspired by existing experience with GEMs, DTs and meteorological models.

Most importantly, a new type of training data must be collected, an undertaking that will require substantial financial resources and time. To address this, we recommend beginning with the design and deployment of new sensory instruments capable of collecting the same information that organisms use to perceive their surroundings. Some of the necessary technologies are already available. The data gathered by prototypes of these instruments could be used to train experimental DL models for further study of the prospects of an approach based on DL for predicting ecological community change.

However, it should be clear that designing and building the architecture of the entire pipeline for using DL in ecology, from data collection and preparation (Lu et al. 2026) to selecting and developing sub-models for constraining DL to realistic predictions and interconnecting DL algorithms, training and testing them and fine-tuning hyperparameters, that is, the parameters of the configuring parts of the model's learning process (Christin et al. 2019), is a massive undertaking (McIntire et al. 2022). Kitzes et al. (2025) outline the complex decisions involved in developing such a pipeline for terrestrial bioacoustics research. Successful application will require collaboration amongst experts from various disciplines (Bogoni et al. 2025).

When combined with models that simulate environmental changes and after rigorous testing of all sub-models, we believe that these DL models will eventually be capable of predicting changes in ecological communities. Such predictions would extend our ecological knowledge profoundly and, when available at the relevant spatial and temporal scales, may provide the accurate scenarios needed by nature conservation policy-makers to make informed, trustworthy decisions about conservation strategies.

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Additional information

Conflict of interest

The authors have declared that no competing interests exist.

Ethical statement

No ethical statement was reported.

Artificial Intelligence (AI) use

The authors accept full responsibility for the content of the manuscript, including the disclosure of any use of AI.
Regarding the use of AI in the preparation of this manuscript, the authors declare the following: GPT.
Used for: Language, style and writing.
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Author contributions

Both authors conceived the ideas, CM wrote the first draft, both authors contributed critically to the drafts and gave final approval for publication.

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Data availability

All of the data that support the findings of this study are available in the main text.