1 # **Applications for Deep Learning in Ecology**

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7 **Abstract**

8 A lot of hype has recently been generated around deep learning, a group of artificial intelligence

9 approaches able to break accuracy records in pattern recognition. Over the course of just a few years,

10 deep learning revolutionized several research fields such as bioinformatics or medicine. Yet such a

11 surge of tools and knowledge is still in its infancy in ecology despite the ever-growing size and the

12 complexity of ecological datasets. Here we performed a literature review of deep learning

13 implementations in ecology to identify its benefits in most ecological disciplines, even in applied

14 ecology, up to decision makers and conservationists alike. We also provide guidelines on useful

15 resources and recommendations for ecologists to start adding deep learning to their toolkit. At a time

16 when automatic monitoring of populations and ecosystems generates a vast amount of data that cannot

17 be processed by humans anymore, deep learning could become a necessity in ecology.

18 **Keywords**

19 Deep Learning, Neural Network, Ecology, Automatic Monitoring, Pattern Recognition, Artificial

20 Intelligence

21 ## **Introduction**

22 Over the course of just a few years, deep learning, a branch of machine learning, has permeated into

23 various science disciplines and everyday tasks. This artificial intelligence discipline has become

24 increasingly popular thanks to its high flexibility and performance. For instance, deep learning

25 algorithms broke accuracy records in image classification[1] or speech recognition[2]. Deep learning is

26 rapidly expanding, revolutionizing the way we use computer power to automatically detect specific

27 features in data and to perform tasks such as classification, clustering or creating predictive models[3].

28 Applications for these tools now span scientific and technological fields as varied as medicine[4,5],

29 bioinformatics[6], finance[7], but also automotive engineering (e.g. self-driving cars[8]), robotics[9], or even

30 video games[10]. Such a surge of tools and knowledge provided by deep learning could also be valuable

31 in ecology as well, yet its use is still limited in this field and overview of its potential in ecology is

32 warranted.

33 Overall, machine learning tools, not just deep learning ones, are interesting for ecologists because they

34 are able to analyze complex nonlinear data, with interactions and missing data, a type of complexity

35 frequently encountered in ecology[3,11]. Machine learning has already been successfully applied to

36 ecology to perform tasks such as acoustic classification[12], ecological modelling[13] or studying animal

37 behaviour[14]. What makes deep learning so powerful resides in the way it can learn features from data.

38 Machines can be taught in two main ways. They can learn without supervision where computers try to

39 automatically detect patterns and similarities in unlabelled data. With this method, no specific output is

40 expected and this is often used as an exploratory tool to detect features in data, reduce its number of

41 dimensions or cluster similar groups[14]. For detection, identification or prediction tasks, learning is

42 usually done with supervision. A labelled dataset with the objects to recognize is first given to the

43 computers so they can train to associate the labels to the examples. They can then recognize and

44 identify these objects in other datasets[15]. However, with conventional machine learning, it is not enough

45 to just provide labels. The user also needs to specify in the algorithm what to look for[3,15]. For instance,

46 to detect giraffes in pictures, characteristics of giraffes will need to be programmed for the algorithm to

47 be able to recognize them. This can hamper non-specialists of machine learning because it usually

48   requires a deep knowledge of the studied system and good programming skills[15]. In contrast, deep

49   learning methods skip such a step. By using general learning procedures, deep learning algorithms are

50   able to automatically detect and extract features from data[15]. This means that we only need to tell a

51   deep learning algorithm whether a giraffe is present in a picture and, given enough examples, it will be

52   able to figure out by itself what a giraffe looks like. This is made possible by creating a multi-layered

53   decomposition of the data with different levels of abstraction that allow the algorithm to learn complex

54   functions representing the data[15]. This ability to auto-detect features in complex, highly dimensional

55   data, with highly predictive accuracy is what led to the fast expansion and ubiquity of deep learning

56   methods[15]. And the numerous levels of ecology (from individual to meta-ecosystem scales) should not

57   be different from the highly dimensional data deep learning is especially accurate and efficient at.

58   Box 1**: Deep neural networks architectures**

59   Considering the complexity of ecological data and the ever-growing size of ecological datasets, a

60   phenomenon recently amplified by the widespread use of automatic recorders[16,17], we believe that deep

61   learning can be a key tool for many ecological analyses. Yet, the mathematical complexity and the

62   programming skills required to implement such a tool might be intimidating and prevent ecologists to

63   use it. Besides, to our knowledge, no paper provides an insightful overview on when a deep learning

64   tool could be useful to ecology. Here we perform a literature review of deep learning implementations

65   in ecology to identify its benefits in most ecological disciplines, even in applied ecology, up to decision

66   makers and conservationists alike. We also provide useful insight and resources to help ecologists

67   decide whether deep learning is an appropriate method of analysis for their studies.

68

69   **Methods**

70   We performed a review of articles that use deep learning methods for ecological studies or that describe

71   methods that could be used in ecological studies such as animal or plant identification or behavioural

72   detection.

73   Our literature review was performed on April 4th 2018 using four search engines, i.e. *Web of Science,*

74   *Science Direct, arxiv.org* and *bioRxiv*. While some articles that have not yet been reviewed by peers can

75   be found in the last two databases, we decided to include them (n= 26) because the widespread use of

76   deep learning is still very recent, the value of their study is clear, and the publishing process can

77   sometimes be long. Our goal here was not to validate the science behind the studies but to provide

78   examples and ideas on how to use deep learning in ecology. Doing so allowed us to have the most up-

79   to-date information about research in progress and/or made public. If a published version of an article

80   found on a preprint server was available, this version was selected. When available, we restricted our

81   search to categories relevant to ecology. Otherwise, the keyword "ecology" was added to the search

82   terms. We performed three searches in each website with the following keywords: 1) "deep learning"

83   AND algorithm; 2) "convolutional neural network"; 3) "recurrent neural network". These two types of

84   deep learning methods were chosen, as they are currently the two most popular methods in deep

85   learning across disciplines. The list of all returned papers can be found at

86   https://figshare.com/s/9810c182268244c5d4b2.

Results

87   In total, 74 unique articles were found. We narrowed down our selection of studies by reading all or

88   parts of each paper found and selected 39 papers that described research related to ecology or that

89   could be of use for ecologists. Eleven (11) papers were added after searching for articles within the

90   reference list of the selected papers. Almost two thirds of the selected papers (n = 32, 64 %) were

91   published in 2017 or 2018 (Figure 1), showing the recent interest in the method. Of all 50 selected

92   papers, 46 implemented at least one deep learning model, with one implementing two – a CNN and a

93   RNN[18]. The remaining papers only mentioned or discussed the use of deep learning for ecological

94   studies.

95   **Figure 1:Repartition of deep learning implementations in ecology by year and architecture.**

96   Since deep learning was popularized by the performance of convolutional neural network (CNN) on

97   image recognition[1], it is not surprising that CNNs are the dominant implementation in ecology (Figure

98   1) and that more than half of the studies (n = 25, 54%) exploit deep learning for image processing.

99   Other uses include sound processing (n = 7, 15%) or modelisation (n = 10, 22%). Architectural

100   differences between RNN and CNN explain why the former have been used for longer (Box 1).

101   Deep learning methods have already proven to provide good results in a wide range of applications

102   (Figure 2). The next sections provide an in-depth review of some areas of ecology that can benefit from

103   such tools.

104   **Figure 2: Examples of deep learning applications in ecology depending on the study scale**

105   **Identification and classification**

106   With the advent of automatic monitoring, ecologists can now accumulate a large amount of data in a

107   short amount of time. However, extracting relevant information from the large recorded datasets has

108   become a bottleneck, as doing it manually is both tedious and time consuming[19,20]. Automating the

109   analysis process to identify and classify the data has therefore become necessary and deep learning

110   methods have proven to be an effective solution. In fact, all top methods from the LifeCLEF 2017

111   contest, an event that aims to evaluate the performance of state-of-the-art identification tools for

112   biological data, were based on deep learning[21]. CNNs have already successfully been used to identify

113   plants from images of their leaves[22,23] and digitized images of herbaria[24]. CNNs could thus prove to be

114   useful tools for taxonomists. They have also been used to classify acoustic data such as bird songs[25–27],

115   marine mammals vocalizations[28], and even mosquito sounds[29].

116   Use of deep learning has also been successfully used in plant phenotyping, i.e. classifying the visible

117   characteristics of a plant to link them to its genotype. Applications include counting leaves to assess the

118   growth of the plant[30], monitoring the root systems of plants to study their development and their

119   interaction with the soil[31] or counting wheat spikelets[32]. While mainly used in agricultural research so

120   far, there is no doubt that these techniques could be transposed in ecology, for example to study the

121   productivity of an ecosystem or to measure the impacts of herbivory on plant communities.

122   **Behaviour studies**

123   Deep neural networks could prove to be valuable assets to study the behaviour of animals by providing

124   a means to automatically describe their activities. Insight on the social behaviour of individuals could

125   then be gained by describing their body position and tracking their gaze[33,34]. Images from camera

126   trapping can be used to describe and classify the activities of wild animals such as feeding or resting[20].

127   Collective behaviour and social interactions of species such as bees can be studied by using CNNs to

128   locate and identify marked individuals[35].

129   As telemetry datasets are growing bigger every day, deep learning can be used to detect activity

130   patterns such as foraging. Indeed, by training a CNN with GPS localizations coupled with time-depth

131   recorder data used to detect the diving behaviour of seabirds, a research team has been able to predict

132   diving activities from GPS data alone[36].

133   Models of animal behaviour can also be created. By analyzing videos of nematode worms (*C. elegans*),

134   a recurrent neural network was able to generate realistic simulations of worm behaviours. The model

135 could also be used as a classification tool[37]. RNNs also allowed the theoretical simulation of courtship

136 rituals in monogamous species[38] and of the evolution of species recognition in sympatric species[39].

Population monitoring

138 As deep learning can detect, identify and classify individuals in automatic monitoring data, it can also

139 be used to help monitor populations. For instance, population size can be estimated by counting

140 individuals[20], or by using estimation methods such as distance sampling[40]. By extension, information

141 such as population distribution or density can also be calculated from this data as it has already been

142 done with traditional methods[16].

143 Detecting symptoms of diseases is a large potential provided by deep learning. For example, CNNs

144 already help detect plant diseases in olive trees[41], cassavas (*Manihot esculenta*)[42] or various crops[43].

145 While the primary use has been directed towards agricultural applications, this could also be widely

146 applied to wild plant and animal populations to help find hints of scars, malnutrition or the presence of

147 visible diseases like mange[44].

Ecological modelisation

149 Ecologists often require powerful and accurate predictive models to better understand complex

150 processes or to provide forecasts in a gradually changing world[3]. Machine learning methods have been

151 shown to show great promise in that regard[3,11], and deep learning methods are no exception. A deep

152 neural network has recently been able to accurately create distribution models of species based on their

153 ecological interactions with other species[45]. With enough data, methods such as deep Boltzmann

154 machines could become the avenue for studying ecological interactions[46].

155 Deep networks have the potential to model the influence of environmental variables on living species

156 even though they have not yet been applied in this way. Studies in the medical field managed to predict

157 gastrointestinal morbidity in humans from pollutants in the environment[47,48], a method that could easily

158 be transferable to wild animals. Recurrent networks have also been shown to successfully predict

159 abundance and community dynamics based on environmental variables for phytoplankton[49–51] and

160 benthic communities[52]. Overall, with functionality in predicting species distribution and environmental

161 predictors, this means that deep learning could be part of the toolbox of ecological niche models.

162 **Ecosystem management and conservation**

163 With human activities affecting all ecosystems, a major task for ecologists has been to monitor and

164 understand these ecosystems and their changes for management and conservation purposes[53]. We argue

165 here that deep learning tools are appropriate methods to fulfill such aims. For instance, biodiversity in a

166 given site can be estimated via the identification of species sampled in automatic recordings[54]. Beyond

167 species identification, the timing of species presence in any given site can also be measured with time

168 labels tailored to species lifecycles[20]. The functioning and stability of ecosystems can then be

169 monitored by converting all these species data and interactions into food web models and/or focusing

170 on indicator species such as bats, which are very sensitive to habitat and climate change[55].

171 With respect to habitat management, new examples have just been described. By being able to model

172 the dynamics of phytoplankton and benthic communities from environmental variables, deep networks

173 provided a tool to monitor and improve water quality management[49,51,52].

174 Deep learning is also perfect to perform landscape analysis for large scale monitoring. For instance, in

175 order to monitor coral reefs, CNNs have been trained to quantify the percent cover for key benthic

176 substrates from high-resolution reef images[56]. Events that modify the landscape such as cotton blooms

177 are detectable using convolutional networks and aerial images[57]. And by combining satellite imaging,

178 LIDAR data and a multi-layer neural network, the aboveground carbon density was quantified in order

179 to define areas of high conservation value in forests on the island of Borneo[58].

180   Beyond mapping species and areas of high value for ecosystems and conservation, deep learning has a

181   large set of potential applications to track the impacts of human activities. Recently, deep neural

182   networks mapped the footprint of fisheries using tracking information from industrial fishing vessels[59].

183   And in order to reduce illegal trafficking, it has been suggested to use deep learning algorithms to

184   monitor such activities on social media to automatically detect pictures of illegal wildlife products[60].

185   To go even further, deep learning has already been envisioned as a cornerstone to create fully

186   automated system designed to create and manage wild ecosystems[61]. Data gathered by automated

187   sensors would be sent to a deep learning algorithm that could then take decisions such as reseeding by

188   using drones or eradicating invasive species with robots. Such systems would allow continuous

189   ecosystem management without requiring any human intervention[61]. While this type of large-scale

190   automatic systems is seen on the applied perspective, we could suggest a fundamental use aiming at

191   mapping and studying biodiversity patterns and processes across various ecosystems.

192   **Box 2: Deep learning toolkit**

193   **Challenges to apply deep learning in ecology**

194   While deep learning methods are powerful and promising for ecologists, it is also important to

195   remember that these tools also have requirements that need to be considered before deciding to

196   implement them. Here are some of the major difficulties that can be encountered when dabbling in deep

197   learning waters.

198   Perhaps the biggest challenge for deep learning lies in the need for a large training dataset to achieve

199   high accuracy. Algorithms are trained by examples and the machine can only detect what has been

200   previously shown to her. This implies that training datasets must often need thousands to millions of

201   examples – depending on the task – with bigger datasets giving better results[62]. This also implies that

202   the dataset we want to analyze must have a consequent size and that finding the right threshold of size

203   is critical. For instance, in acoustic processing, at least 36 hours of recording are required for a deep

204   learning algorithm to become more efficient than human listening [25]. Although this is a challenge in its

205   own, the good news is, it is now relatively easy to gather hours and hours of acoustic recordings[63].

206   To help alleviate the need for data-hungry training examples, multiple solutions have appeared in

207   recent years and are readily available in ecology. A popular choice is transfer learning[64]. Transfer

208   learning consists of pre-training a model to detect specific features tailored to the type of data to

209   process on a large dataset with similar characteristics. For instance, a user who wants to detect objects

210   in pictures but has a limited annotated set can first pre-train his model on a large public image dataset,

211   even if the images are unrelated to the objects to detect (Box 2). The model can learn to detect features

212   like edges or colours[64], and can be then trained on the smaller dataset containing the objects to

213   recognize. To save time, it is even possible to directly download the results of pre-training on large

214   public image datasets for some popular implementations of CNN[64]. Another way to help feed the model

215   with enough data is data augmentation. Data augmentation consists in the artificial generation of more

216   data for training from annotated samples. For instance, with sound recordings, noise can be added or

217   the sound distorted. With images, colours can be altered or the images flipped or rotated. This allows

218   not only a greater variety of data to be fed to the model but also a sufficient quantity to be provided for

219   efficient training. Deep learning can even be used to generate realistic datasets for training. This

220   method has been applied to successfully generate plant images[65,66] or bee markers[67].

221   Training on very large datasets also comes with another requirement: computing power. To effectively

222   train a deep learning algorithm, it will need to learn millions of parameters[68]. To achieve that, very

223   powerful hardware resources are needed. In fact, the recent explosion in deep learning has been made

224   possible to the technological advancement in computer hardware and especially the use of graphics

225   processing units (GPU) found in graphic cards[69] (Box2). The good news is that training a deep learning

226   algorithm can technically be done on any recent hardware, allowing any ecologists with a reasonably

227   powerful laptop to do it. However good graphics cards can speed up the training time by orders of

228   magnitude[69]. Even then, training the model can take several days to converge for very complex

229   analyses and fine tuning the model for improved accuracy could require several training sessions[25,68].

230   Nevertheless, once the training is done, the model created is generally quite performing and capable of

231   going through large datasets efficiently compared to other alternative approaches, thus leading to time

232   savings[25].

233   Another common problem with deep learning is that it has limited potential for solving a task it was not

234   designed and trained for[62]. For instance, if we design an acoustic recognizer to identify a particular

235   species from its calls, it will have a hard time recognizing taxonomically distant species calls. At the

236   moment, the easiest way to solve this would be to increase the training dataset size to include samples

237   of other species of interest, signalling the need for linking deep learning and more traditional analysis

238   approaches.

239   **Concluding remarks**

240   Deep learning, just like other machine learning algorithms, provide useful methods to analyze

241   nonlinear data with complex interactions and can therefore be useful for ecological studies. But where

242   deep learning algorithms really shine lies in their ability to automatically detect by themselves objects

243   of interest in data – such as animals in pictures – just by knowing whether the object is present or not.

244   Moreover, they can do that with great accuracy, making them choice tools for identification and

245   classification tasks. While the emphasis has been on so far supervised methods due to their

246   performance and ease of training, future developments in unsupervised learning are expected, thus

247   potentially removing the need for annotated datasets altogether [15].

248 Deep learning shows a lot of promise for ecologists. While the popularity of the method is still very

249 recent, implementations are already covering a wide array of ecological questions and can prove very

250 useful tools for managers, conservationists or decision makers by providing a fast, objective and

251 reliable way to analyze huge amounts of monitoring data. Applications can also go beyond ecology and

252 deep learning could also be valuable to evolutionists or biologists in general. However, developing a

253 deep learning solution is not a trivial task yet and ecologists do need to take time to evaluate whether

254 this is the right tool for the job. Requirements in terms of training datasets, training time, development

255 complexity and computing power are all aspects that should be considered before going down the deep

256 learning path.

257 As ecology enters the realm of big data, relying on artificial intelligence to analyze data will become

258 more and more common. Ecologists will then have to acquire or have access to good programming

259 and/or mathematical skills. While this might seem scary at first sight, we believe that there is one

260 simple solution to this challenge: collaboration across disciplines. A stronger interaction between

261 computer scientists and ecologists could unravel new synergies and approaches in data classification

262 and analyses, deepening our understanding of fundamental and applied research in ecology. This in turn

263 would allow ecologists to focus on the ecological questions rather than on the technical aspects of data

264 analysis and computer scientists to delineate new avenues on some of the most complex data and units

265 of our biological world such as ecosystems. We also strongly encourage sharing datasets and codes

266 whenever possible to make ecological research faster, easier and directly replicable in the future,

267 especially when using complex tools such as deep learning. With software getting more powerful and

268 easier to use, experience being accumulated and shared and resources such as datasets made available

269 to everyone, we believe that deep learning could become an accessible and powerful reference tool for

270 ecologists.

271

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277 S.C. and N.L. had the original idea for the study and designed the research. S.C., N.L., and E. H.

278 collected the review information and carried out the analyses. S.C., N.L. wrote the first drafts of the

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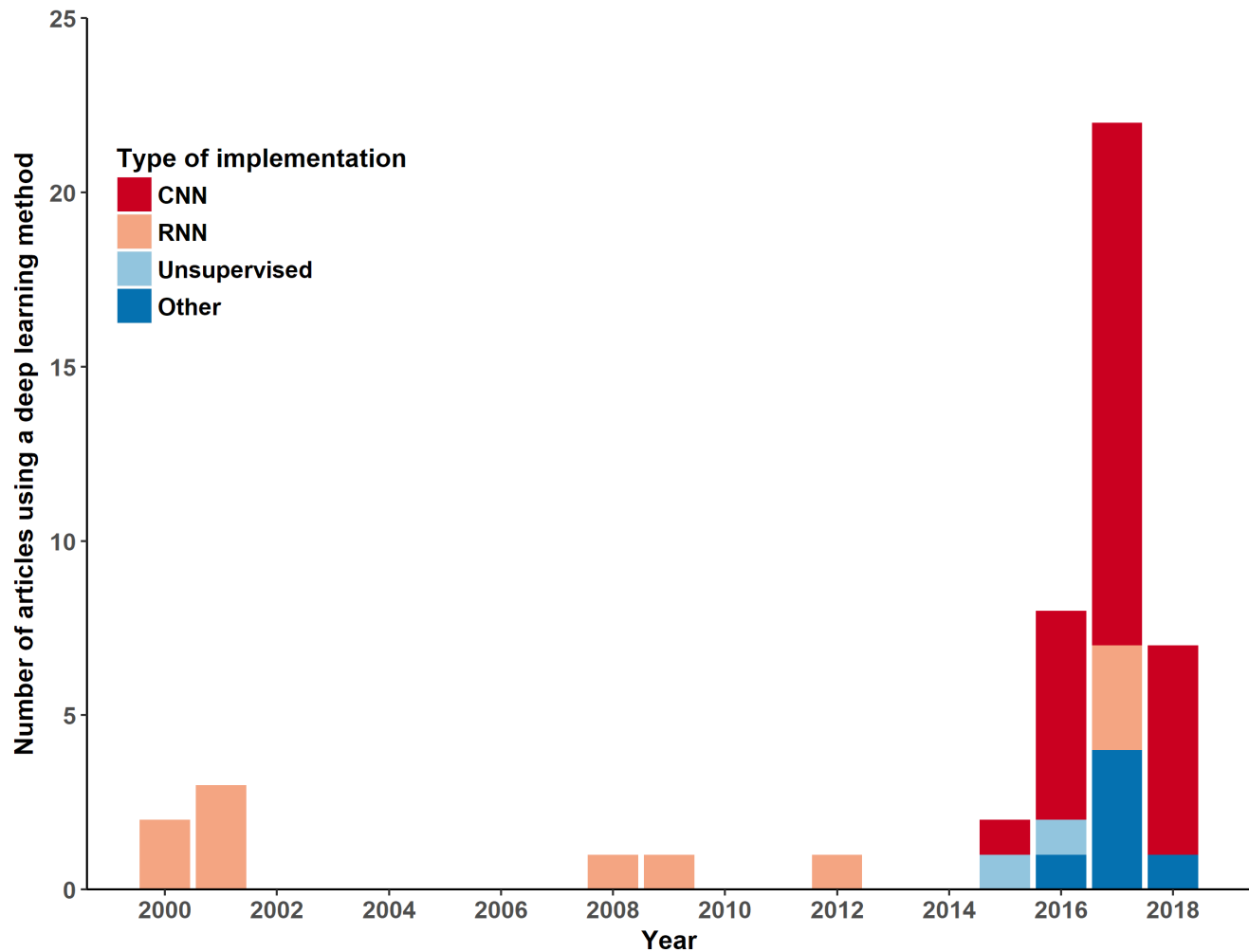
Figure 1: Repartition of deep learning implementations in ecology by year and architecture.
Implementations were grouped in 4 categories: convolutional neural networks (CNN), recurrent neural networks (RNN), and unsupervised methods. The "Other" category includes studies where classification of the type of algorithm was either difficult to identify or undisclosed. Note that one study[18] was counted twice as it implemented a combination of CNN and RNN.
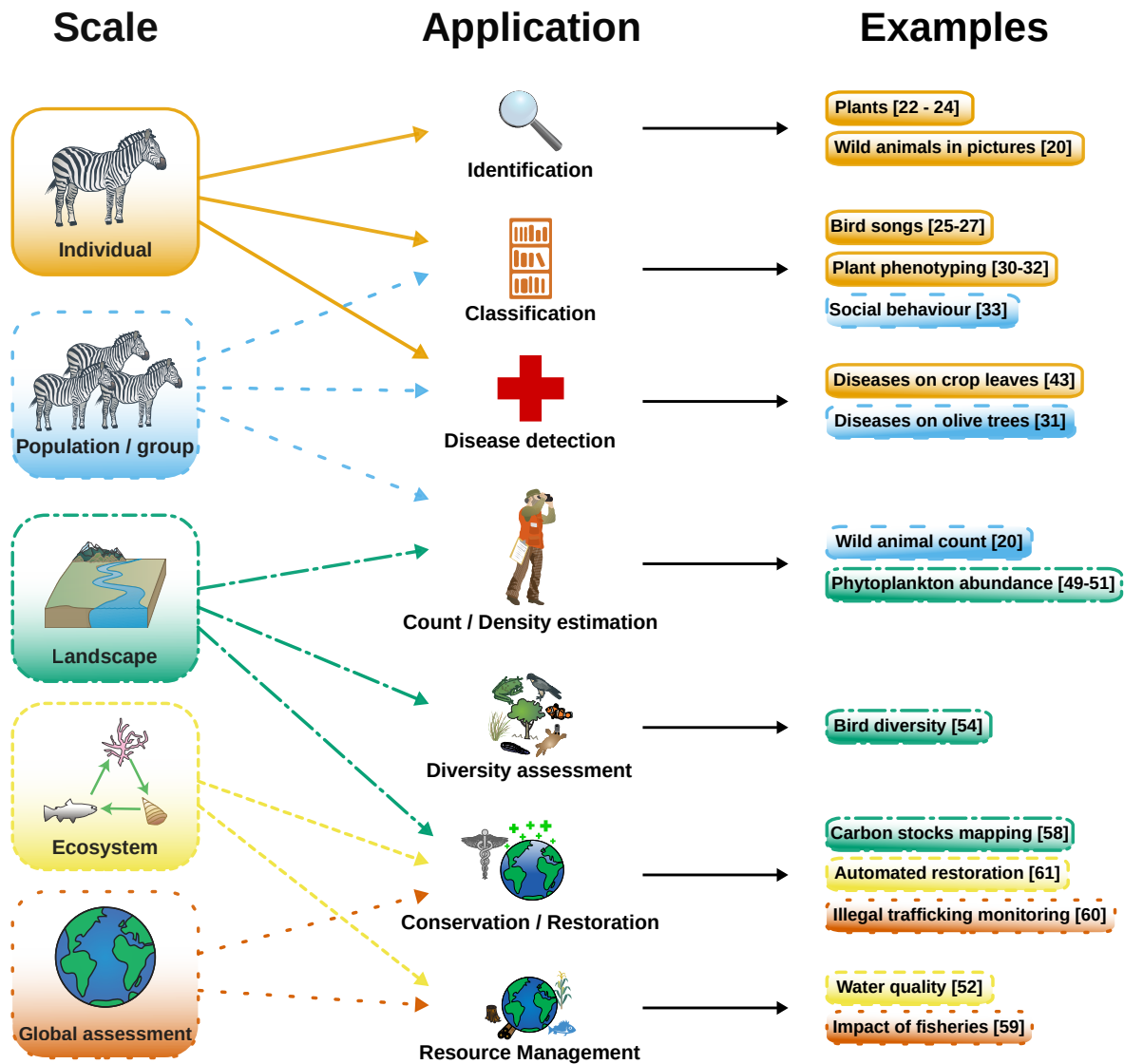
Figure 2: Examples of deep learning applications in ecology depending on the study scale

283 **Box 1: Deep neural networks architectures**

284 From a technical standpoint, deep learning algorithms are multilayered neural networks. Neural

285 networks are models that process information in a way inspired by biological processes, with highly

286 interconnected processing units called neurons working together to solve problems[3,11](Figure I). Neural

287 networks have three main parts: 1) an input layer that receives the data, 2) an output layer that gives the

288 result of the model, and 3) the processing core that contains one or more hidden layers. What

289 differentiates a conventional neural network from a deep one is the number of hidden layers, which

290 represents the depth of the network. Unfortunately, there is no consensus on how many hidden layers

291 are required to differentiate a shallow from a deep neural network[69].

292 During training, the network adjusts its behaviour in order to obtain the desired output. This is done by

293 computing an error function by comparing the output of the model to the correct answer. The network

294 then tries to minimize it by adjusting internal parameters of the function called weights, generally by

295 using a process called gradient descent[15].

296 Among deep networks, several structures can be found. Feedforward networks map an input of

297 determined size (e.g. an image) to an output of a given size (e.g. a classification probability) by going

298 through a fixed number of layers[15]. One of the feedforward implementation that received the most

299 attention due to its ease of training and good generalization is the convolutional neural network (CNN).

300 CNNs are designed to process multiple arrays of data such as colour images and generally consist of

301 stacking groups of convolutional layers and pooling layers in a way inspired by biological visual
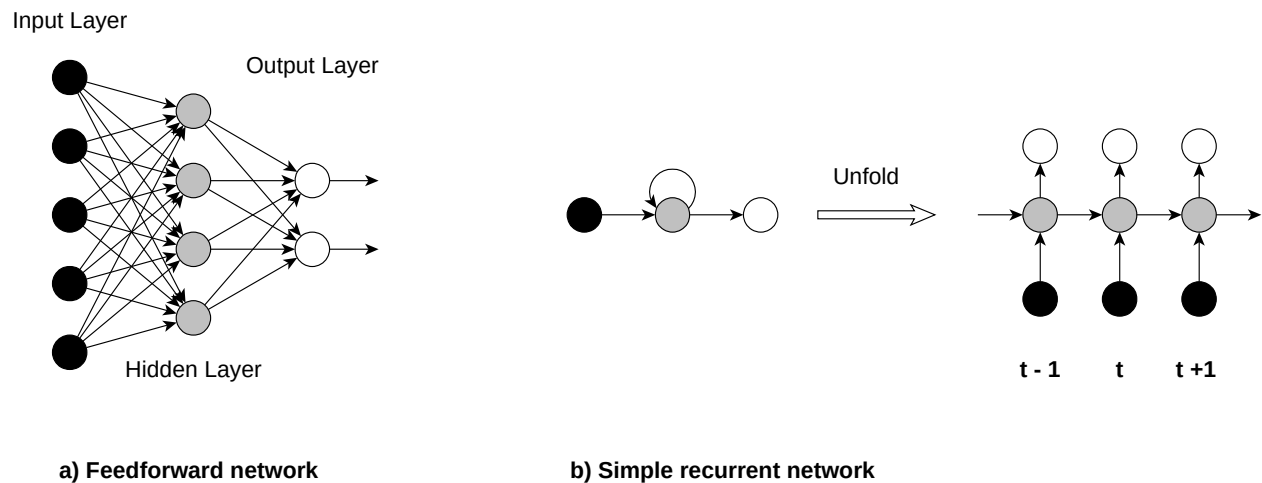
302 systems[15].

Input Layer

Output Layer

Unfold

Hidden Layer

t - 1   t   t +1

a) Feedforward network   **b) Simple recurrent network**

Figure I: Architecture of common neural networks. a) Feedforward networks are unidirectional, from the input layer to the output layer and through hidden layers. Deep feedforward networks have usually at least three hidden layers. b) Simple recurrent neural networks get input from previous time steps and can be unfolded to feedfoward networks

303 Recurrent neural networks (RNN) usually have only one hidden layer but they process elements in

304 sequence, one at a time and keep a memory of previous elements, with each output included in the

305 input of the next element[15]. The summation of each individual step can thus be seen as one very deep

306 feedforward network. This makes them particularly interesting for sequential input such as speech or

307 time series [15]. A popular implementation of RNN is the Long Term Short-Memory network (LSTM), an

308 architecture capable of learning long-term dependencies that has proven especially efficient for tasks

309 such as speech recognition[70] or translation[71].

310 **Box 2: Deep learning toolkit**

311 Here we provide some resources that might be useful in order to successfully create and deploy a deep

312 learning tool.

313 Libraries and packages:

314 With the rapid development of deep learning, a great number of libraries and packages have been

315 created to set a deep network with minimal effort. Most of the popular tools are open source and

316 packages are available in multiple programming languages such as Python, R, Java, Javascript,

317 MATLAB or C++. Note, however, that Python seems to be the most popular programming language for

318 deep learning at the moment (Table I). Keep in mind that most of these tools are currently in active

319 development and could therefore evolve rapidly.

Table I: List of deep learning frameworks and their language

Framework	Language	URL
Tensorflow	Python, C/C++, R, Java, Go, Julia	https://www.tensorflow.org/
Caffe	Python	http://caffe.berkeleyvision.org/
PyTorch	Python	https://pytorch.org/
Deeplearning4J	Java, Scala	https://deeplearning4j.org/
Keras	Python, R	https://keras.io/
MATLAB + Neural Network Toolbox	MATLAB	https://www.mathworks.com/products/neural-network.html
Apache MXNET	C++,Python,Julia,Matlab,JavaScript,Go,R,Scala,Perl	http://mxnet.incubator.apache.org/
PlaidML	Python	https://github.com/plaidml/plaidml

320 Graphic cards

321 While optional, deep learning benefits a lot from the use of graphics processing units (GPU) to speed

322 up training. However, at the moment of writing, the market of deep learning is mostly dominated by the

323 manufacturer nVidia, who offers cards specially designed for deep learning applications. Therefore,

324 while some deep learning framework – such as plaidML – support all graphics card, most frameworks

325   only offer GPU acceleration for graphics cards created by nVidia. Fortunately for researchers, a grant

326   program exists to offer free graphics cards to promote research with deep learning.

327   Other useful resources

328   **Github.com:** a website originally designed as a tool to freely share and keep track of change in

329   programming code. By promoting open source collaboration, github provides not only a great way to

330   save your code but also a reference database in which examples and tools can be found.

331   **Kaggle.com**: A data science website that allows you to host competitions to get the best machine

332   learning models suited to your data. By providing training and reference datasets, the expected results

333   and offering a reward, data scientists can create for your deep learning models without you having to

334   learn how to do it. It also provides a useful source of information, examples, reference databases as

335   well as access to an experienced community for those who want to learn more about deep learning by

336   themselves

337   Reference databases:

338   Public annotated databases can increasingly be found online in order to facilitate the training of deep

339   neural networks in ecology. Some of them include bird sounds such as the Macaulay

340   (https://www.macaulaylibrary.org/) or Xeno-Canto (https://www.xeno-canto.org/) libraries, bat calls[55],

341   plants[65], or animal images[72]. More generalist reference databases are also available to pre-train neural

342   networks such as MNIST (http://yann.lecun.com/exdb/mnist/) or ImageNet (http://image-net.org/).

343   As scientists are increasingly required to render their research data available, training datasets will

344   become easier to come by in the near future; and the recent surge in data repositories facilitate data-

345   hungry analyses. Some journals such as Scientific Data even focus solely on the publication of research

346   datasets[73].