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Research

Putting machine learning to use in natural resource management—improving model performance

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ABSTRACT. Machine learning models have proven to be very successful in many fields of research. Yet, in natural resource management, modeling with algorithms such as gradient boosting or artificial neural networks is virtually nonexistent. The current state of research on existing applications of machine learning in the field of social-ecological systems is outlined in a systematic literature review. For this purpose, a short introduction on fundamental concepts of neural network modeling is provided. The data set used, a prototypical case study collection of social-ecological systems—the common–pool resources database from the Ostrom Workshop—is described. I answer the question of whether neural networks are suitable for the kind of data and problems in this field, and whether they or other machine learning algorithms perform better than standard statistical approaches such as regressions. The results indicate a large performance gain. In addition, I identify obstacles for adapting machine learning and provide suggestions on how to overcome them. By using a freely available data set and open source software, and by providing the full code, I hope to enable the community to add machine learning to the existing tool box of statistical methods.

Key Words: *comparability; gradient boosting; machine learning; natural resource management; neural networks; social-ecological systems*

INTRODUCTION

By now, machine learning algorithms have proven themselves as powerful problem-solving tools in many domains. Examples include complex strategy games like chess and Go (Silver et al. 2017), strategic decisions under uncertainty against human players—e.g., poker (Brown and Sandholm 2019)—or complex cooperative games (Mnih et al. 2015). Other areas include autonomous driving, translations in many languages via a universal interlingua (Johnson et al. 2017), and image recognition (multiclass object detection) in the millisecond range, beating human performance (Le et al. 2012, Girshick 2015).

For many scientific domains, the question arises as to whether and how these advances in machine learning can be applied to their own research questions. It has become apparent that application of machine learning algorithms varies greatly between individual disciplines. In particular, in the fields of natural resource management and social-ecological systems it seems that machine learning methods are still used rather infrequently. However, applying machine learning algorithms to natural resource management problems may result in various benefits: improving explanatory power for many models—thus, for example, being better able to distinguish important from irrelevant factors for successful management; generating more robust results by using different algorithms with the same workflow (see *Discussion*), and finally, providing an extension to the toolbox of methods for analyzing case studies.

Given that machine learning algorithms have demonstrated their potential for modeling in many fields (LeCun et al. 2015), I aim to estimate the potential of machine learning methods, especially deep neural networks, for modeling natural resource systems. I evaluate the general suitability or unsuitability in both theory (through a literature review) and practice (a systematic search for neural network architectures for a typical data set). By assessing the potential of machine learning in natural resource research and by summarizing the state of research and best practices as well as directions, future research may profit. Such evaluations have also been done for other research fields such as biology and medicine (Ching et al. 2018).

The next section of this article outlines the state of research on existing applications of machine learning in the fields of social-ecological systems, (community-based) natural resource management, and common-pool resources in order to assess for which problems other authors have applied machine learning methods.

The *Data* section describes the data set used, a prototypical case study collection from social-ecological systems—the common-pool resources database from the Ostrom Workshop (n = 122). In the *Results* section, I discuss whether deep neural networks perform better than other methods in terms of model quality (goodness-of-fit). By comparing different architectures, it will become clear which kinds of networks may serve as a base for improved models in the future. After that, in the *Discussion*, I review whether neural networks could indeed be a methodological step forward in the area of natural resource management.

The *Methods* section provides a short introduction on fundamental concepts of neural network modeling in order to facilitate future analyses. A prototypical data set is analyzed by using many different variations (architectures) of neural networks to establish the general suitability of this method for natural resource management data.

To make the agenda more concrete, I strive to answer three research questions, in particular: "

1. Can shallow or deep neural networks achieve a decisive improvement in model quality compared to previously employed statistical techniques such as linear regressions?"

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2. Are there architectures that are particularly suited for the analysis of social-ecological systems?"
3. Are other machine learning methods suited to deal with social-ecological case study collections?

State of research

One of my goals was to evaluate whether and how machine learning methods have already been used in the fields of natural resource management and social-ecological systems (e.g., Humphries et al. 2018). Hence, in order to gain an overview, a systematic literature analysis was conducted on 19–21 November 2019 and 23 November 2020. A keyword search was conducted in more general journals—*Nature*, *Science*, *Proceedings of the National Academy of Sciences of the United States of America*, *Proceedings of the Royal Society*, *Nature Methods*, *Nature Sustainability*, *Nature Climate Change*, and *PLoS ONE*—and in journals that are central to natural resource management (*Ecology & Society*, *Sustainability Science*, *International Journal of the Commons*, *Ecological Modeling*, *Global Environmental Change*, *Journal of Environmental Management*, *World Development*, *Environmental Modeling and Software*, and *Journal of Cleaner Production*). The search was conducted using the internal search engines of each journal.

The keywords that were searched for were “machine learning”, “neural network”, and “deep learning”. For the more general journals, which, in contrast to the topic-specific journals, are not restricted to natural resources, I added to each of the three search terms the keywords “natural resource” or “social ecological”. Using no quotation marks on both search terms resulted in thousands of irrelevant hits (e.g., on learning); using them for both search terms simultaneously was too restrictive and resulted in 0 hits. Some journal search engines interpreted phrases in quotation marks as logical “ORs”, which resulted in many irrelevant hits (e.g., “machine learning” as machine OR learning).

The exact figures for each search combination are provided in Table A1. Typically, searches produced 20–150 hits. These were screened. If a hit seemed to be about any topic in natural resource management and used any kind of machine learning techniques, it was included in the final data set (Table A2). Of course, many other machine learning classifiers and algorithms exist (Elith et al. 2006, Fernández-Delgado et al. 2014). However, I was concerned with only the most widely used algorithms—neural networks, gradient boosting, and generalized linear models—since even they are rarely used for natural resource management problems.

All in all, very few hits were found. Although the first screening resulted in n = 2.616 hits for topic-specific journals and 3.287 for more general journals, only 32 papers were about applying machine learning to natural resources in any way. This was rather surprising given the spectacular advances in other fields. This number proves that machine learning does not yet play a role in natural resource management. I discuss possible reasons for this in the *Discussion* section.

Before discussing the few relevant papers, I note that in many adjacent research fields such as renewable energies (IPCC 2018) or biodiversity research, machine learning methods, in particular neural networks, are used quite frequently. Typical fields of application include, but are not limited to, wind energy potential assessment, species biodiversity models, expansion models of species, spatial habitat modeling, evaluation of remote sensing data, and prediction of solar radiation.

One of the first applications of neural networks for social-ecological systems was provided by Frey and Rusch (2013, 2014). For common-pool resources case studies, shallow neural networks are used to identify success factors. These papers also substantiate the claim often made that neural networks are able to cope better with nonlinearities between features than are regressions (Paruelo and Tomasel 1997). Very similar is the attempt to identify success patterns in fisheries with random forests (Gutiérrez et al. 2011).

Among other uses of machine learning, two prominent topics for applying machine learning are modeling land use change (Cao et al. 2019, Saputra and Lee 2019; for land use change in rivers, see Álvarez-Romero et al. 2015, Magierowski et al. 2015; for classifying habitats, see Václavik et al. 2013), as well as predicting and classifying fishermen behavior (Jules Dreyfus-León 1999, Cenek and Franklin 2017, Crespo et al. 2018, O'Farrell et al. 2019). For further details on these studies, see Table A2 and the *Literature Cited* section.

All in all, neural networks and random forests were the most popular techniques, while content-wise, predictive tasks for spatial patterns dominated. However, there were no commonly adopted workflows or any other kind of standards across papers.

Given these few existing attempts to make machine learning fruitful for natural resource topics, it is even more important to explore in practice whether neural networks can improve model quality. I therefore implemented many neural network architectures to explore this potential in more detail.

Data

The common-pool resources database was chosen for the test of neural networks and the method comparison described in the *State of research* section. It is a typical data set consisting of case studies of irrigation systems and fisheries (n = 122), and is available online (https://seslibrary.asu.edu/cpr). The idea is that it can stand for hundreds of other data sets that have a similar structure concerning number of variables, tabular structure, and concepts involved. Reference data sets are well-known from other fields, one famous example being the MNIST data set (http://yann.lecun.com/exdb/mnist/), which serves as a benchmark for comparing performance of machine learning classifiers. In contrast to other data sets outside natural resource management, it is relatively small, but differences between cases are rather large, which means that pattern recognition via supervised learning is particularly suitable.

The structure of the common-pool resources database was developed at the Ostrom Workshop in Political Theory and Policy Analysis at University Indiana Bloomington. The data have been collected for several years and are the basis for perhaps the most influential analysis on social-ecological systems, *Governing the Commons* (Ostrom 1990). The database comprises about 500 variables that include demographic, geographical, social, cultural, climatic, economic, and technical details of irrigation systems and fisheries worldwide.

There were several reasons for selecting this data set. First, analyses have shown that the data set is typical for social-ecological case studies (Frey 2018). Second, it has a sufficient number of heterogenous cases.

The 593 variables were aggregated; i.e., assigned to 24 abstract concepts, such as social capital, resource size, or participation opportunities. The details of assigning the variables to these concepts can be found in Frey (2018). One benefit of aggregating is that missing variables are no longer problematic, since existing variables within a concept can stand in for variables that are missing.

The dependent variable was ecological success. The variables it is composed of can be found in Table A4. All variables were normalized with zero mean and unit variance. This is a common step in data preparation for neural networks to avoid the problems of exploding and vanishing gradients.

METHODS

Given that neural networks usually work with thousands or even millions of data records, one important question to be answered first is whether neural networks are at all suited to the much smaller data sets that are typical of natural resource management. It is yet unclear if the kind of data that are characteristic of collections of case studies (only a few hundred cases with a few hundred variables that can be aggregated to a few dozen concepts) require neural networks at all. This was one goal of this investigation.

Another important question is whether deep neural networks (with multiple hidden layers between input and output) are a suitable method to use for natural resource management. Perhaps nonmachine learning methods or very simple neural network architectures prove to be sufficient. Hence, I first introduce deep neural network architecture and shallow neural networks (only one hidden layer) before shortly characterizing other methods in order to compare their model fits on this data set, which is typical for case studies with many variables.

By now, a large variety of different architectures for neural networks exist (LeCun et al. 2015). Each type of neural network architecture is adapted to a certain kind of problem. For example, the best results on most image recognition tasks have been achieved using deep convolutional neural networks, whereas Long Short-Term Memory networks have proven to be superior to other architectures on time series analysis tasks (Hochreiter and Schmidhuber 1997). However, in principle, finding the right architecture is a matter of trial and error, especially parameter fine-tuning.

For tabular data, like those used in this article, shallow or simple deep neural networks with only a few layers have achieved good fits (Frey and Rusch 2013). Since other architectures are for other kinds of tasks, mostly highly specific, I have not further tested such architectures and have constrained my tests to feed-forward and deep feed-forward nets.

Fine-tuning such networks involves mainly adapting their hyperparameters. These are the "nuts and bolts" of a network. It is well-known that parameters like number of layers, number of hidden neurons, learning rate, or number of training epochs make a considerable difference for the final goodness-of-fit of a model (LeCun et al. 2015). In fact, besides feature construction or extraction (providing meaningful input data; e.g., by aggregating variables), hyperparameter tuning is one of the core steps of a typical machine learning pipeline.

Again, finding the best combination of parameters is a matter of trial and error. Traditionally, researchers manually tried out the most promising combinations. However, with increasing computing power and ever more complex models, this task has been outsourced to computers. This is called grid search.

There are three types of grid search: first, Cartesian grid search, where a discrete number of parameter choices (e.g., 10, 20, and 30 number of neurons, and 50, 100, and 150 epochs, which results in nine combinations) is calculated. The second type is random grid search, where values of parameters are drawn randomly from a range (e.g., number of neurons between 10 and 30; epochs between 50 and 150). Hence, the number of combinations is not fixed. Typically, the maximum number of models to be calculated is provided as a variable by the user. Third, Bayesian search, where resulting fits of parameter combinations are themselves optimized toward a decreasing error rate. This is not standard and has not yet implemented in most leading software packages (e.g., in Scikit-learn or SciPy in Python [Virtanen et al. 2019] or h2o [LeDell et al. 2020]).

It has been shown that random grid search usually yields better results than Cartesian search, which in turn performs better than manual tuning of parameters (Bergstra and Bengio 2012). Hence, I implemented a random grid search for a large parameter sweep. Since both methods are implemented very similarly in most software packages, changing it often means just changing one parameter. In h2o, for example, the parameter "strategy" of a grid search must simply be switched from "Cartesian" to "RandomDiscrete".

This systematic variation of more than 20,000 models tested (5000 runs x four methods) is necessary for three reasons: "

1. to be sure about the best kind of architecture, in general, for such data sets"
2. to provide very sound starting values for further parameter tuning by other researchers when modeling similar data sets

"

3. to make the state-of-the-art goodness-of-fit for such kinds of models known; this makes it possible to use as a benchmark and a comparison to traditional models

For all models, Table A3 presents an overview of the hyperparameters varied and the actual values of the best model. While more parameters have been tuned, those presented in Table A3 are the most important ones. Thus, for most modelers, it might be sufficient to tune only those—the rest most probably result in only very minor improvements of model quality (< 1–2%).

While my main goal was to explore the untapped possibilities of neural networks for natural resource case study data, it could be that other machine learning algorithms might perform even better. For this reason, I provide a short comparison with another algorithm—gradient boosting, a high-performing variant of decision trees (Breiman 2001*a*), which are perhaps the most widely used machine learning algorithms, since they have a good performance across a wide range of problems and are very robust against noise (Alpaydin 2010). In fact, in the natural resource management literature, as presented in the literature review in the *State of research* section, variants of decision trees are the most frequently used algorithm. Furthermore, their results are easily interpretable and feature importance is readily accessible.

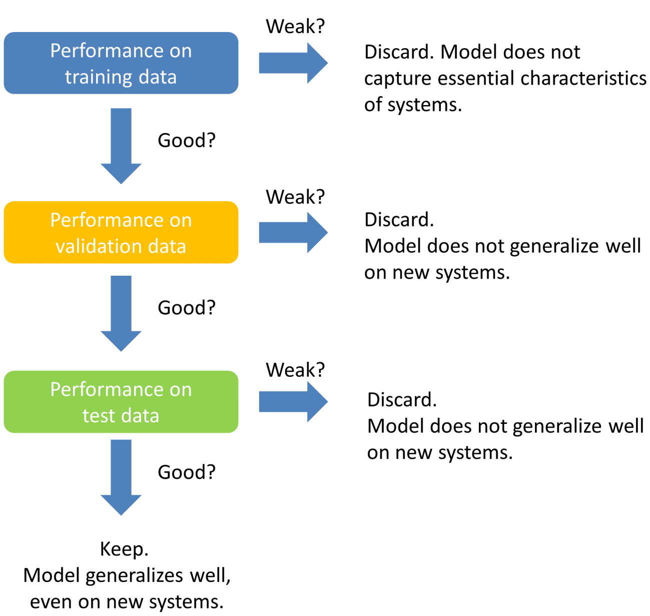
In addition, since most case studies use regressions, I also compared the results with generalized linear models so as to be better estimate the performance boost that could be gained if neural networks are employed in natural resource research. By using a Gaussian distribution, the generalized linear models are identical to multivariate linear regressions, hence, are comparable to existing research. A description of parameters varied during grid search for model optimization are provided in Table A3.

All data were partitioned into two parts—a training (80%) and a test set (20%). This is standard practice in machine learning and is done to avoid overfitting. Overfitting means that a model may perform very well on the training data but is very weak on the new data (the test set) since it does not generalize very well; i.e., it captured too many details present in only the training set but not in the test set.

In addition, a five-fold cross-validation was performed. This means that a different 20% was held out for each of the five models while the training was done on 100% of the data, which was important for such a limited number of cases. Thus, metrics like goodness-of-fit are available for the training, the cross-validation, and the test sets.

I report the metrics of the test sets, which are standard, since they best explain how well the model performed on data it has not encountered before. Fig. 1 explains the workflow used.

Fig. 1. Workflow and relationship between training, validation, and test set.

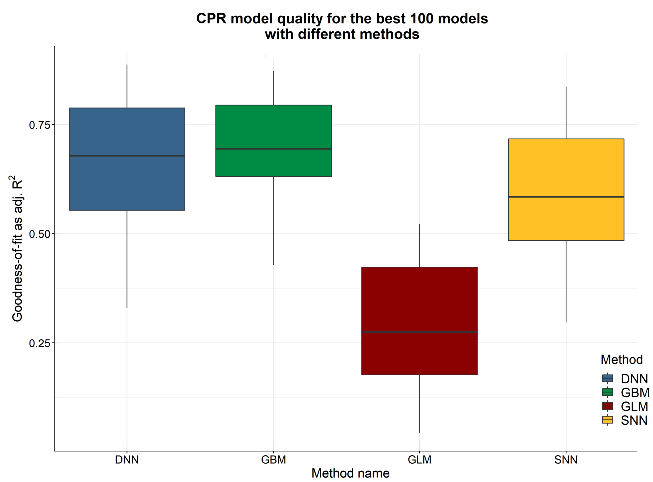


Since one of my goals was to make machine learning more widespread in the community of natural resource management and social-ecological systems, the choice of software was deliberate. I chose h2o, which is open source software (LeDell et al. 2020) and available for several programming languages; i.e., R, Python, and Scala with very similar structure and functions. Hence, adapting the R code in Appendix 1 for any of the major programming languages should be very easy—in fact, a matter of hours at most. It is a standard workflow familiar to any data scientist or machine learning researcher, so further developments should be very easy.

RESULTS

For each method, a random grid search was run for 5000 (500 batches at a time) iterations. Parameters were deliberately of a wide range so as to avoid missing good model parameter combinations ("casting a wide net"). Thus, each run represented a unique combination of parameters. The best 100 models/results for each method were selected (Fig. 2). Each combination of hyperparameters was considered one model.

Fig. 2. Model quality of the best 100 models for four methods (CPR: common-pool resources; DNN: deep neural network; GBM: gradient boosting machine; GLM: generalized linear model; SNN: shallow neural network).



A first result is that model quality, in general, was very high. No median of machine learning models was less than 0.58, and the multivariate regressions were at a median of 0.27 (explanation of variance). The best generalized linear model has a goodness-of-fit of 0.52. As is known from other fields of research, machine learning algorithms are usually very close together in terms of explanatory value. This is true for the top-performing models of my data set with deep neural networks (0.89), gradient boosting machines (0.87), and shallow neural networks (0.84). However, there was a larger gap between the model quality of the regressions and the machine learning algorithms of about 0.32 (Table 1).

A second result is that deep neural networks were a bit better than shallow ones. The more complicated architecture with more hidden layers seems to have been responsible for finding even more

Table 1. Performance comparison of machine learning algorithms on the common-pool resources data set

Performance/machine learning algorithm	Deep neural network	Shallow neural network	Gradient boosting machine	Linear regression (generalized linear model)
Min. test R^2	0.33	0.30	0.43	0.04
Max. test R^2	0.89	0.84	0.87	0.52
Median test R^2	0.68	0.58	0.69	0.27
Mean test MSE	0.015	0.020	0.015	0.035
Min. train R^2	0.92	0.85	0.98	0.28
Max. train R^2	0.99	0.99	0.99	0.66
Median train R^2	0.99	0.96	0.99	0.49
Mean train MSE	0.0005	0.0020	0.0005	0.0250

general patterns in the data. As can be expected with such a small data set, there was some overfitting. However, the algorithms still generalized well on the test sets.

A third result concerns the optimal architecture (Table A3). The best deep neural network had four layers with 492, 13, 85, and 111 neurons, trains for approximately 400 epochs, and has a very high learning rate of 0.12. The number of layers and neurons determines the complexity of the problem the network is able to learn—the more layers and neurons, the more complex. However, there is a trade-off between more layers and neurons and better performance, since training time and computer resources also increase. More problematic than this, however, is that with increasing computing power of the network, overfitting occurs and generalizing abilities decrease. Finally, the learning rate defines the step size with respect to the change of weights. A higher rate means faster progress but may result in nonoptimal weights; a slower rate may result in a long training process and may get stuck in local optima.

Sometimes, combining the best, say for example five models, results in an even better predicting model. This technique of combining is called stacked ensemble. For each kind of machine learning algorithm, I calculated a stacked ensemble, altogether 40 models. However, their predictive power was not higher than the best-performing model. Thus, I do not report these results in further detail.

Hence, the results are clear-cut: "

1. All machine learning algorithms improved model quality in comparison to linear regressions."
2. The boost in model performance ranged from 35 to 40%."
3. Deep neural networks (2–4 layers) increased model quality in comparison to shallow neural networks (one hidden layer only). The adjusted R^2 for this particular data set increased the goodness-of-fit by about 5%."
4. Gradient boosting machines are similar in performance to deep neural networks."
5. Stacked ensembles that combine multiple models did not perform better than the best model for these kinds of tabular data."
6. Model performance varied widely. A large parameter sweep (grid search) was necessary to identify good parameter combinations.

DISCUSSION

This comparative analysis has shown that machine learning methods, in general, and deep neural networks, in particular, may offer significant advantages for the analysis of larger collections of natural resource case studies. However, one limitation of this study is that it is unclear how well one can generalize from this particular data set to other data sets. A limitation of neural networks has been their black box character; yet, with modern algorithms, the influence of independent variables is no longer unknown. They are well capable of estimating each factor independently.

Machine learning methods offer not only substantial model improvements but also decision-making support—e.g., by visualizing the importance of variables in gradient boosting, and thus may help improve ecological sustainability. Their high performance is not surprising given their ability to deal with noisy data and nonlinearities. With various software solutions being available (e.g., Keras in Python or h2o [LeDell et al. 2020]), which no longer require deeper mathematical knowledge about the functioning of neural networks, implementing machine learning algorithms should pose no issues. Nevertheless, a good understanding of the problem and the respective methods that can be applied is necessary; otherwise, the interpretation of results leads to errors. This also applies to the choice of the architecture and the method itself, even if advanced commercial software packages like keras-automl or h2o-automl offer automated workflows.

However, despite these clear advantages, machine learning methods are very rarely applied in natural resource research. I identify three main reasons why:

First, machine learning methods require large amounts of data. Therefore, individual case studies cannot be analyzed; instead, a data collection such as that available in a database is needed. In addition, these data must be fairly complete, since neural networks require complete data as input. Imputation usually leads to poor results. However, most studies deal in detail with one or fewer case studies. The lower limit for neural networks, however, is approximately 100 cases, as the demonstrated in the *State of research* section. Since deep neural networks can play out their advantages mostly for large data sets (e.g., images, text corpora), this may be one reason for the slow use of these techniques.

Second, data—case studies—need to be in a standardized format to be comparable (Frey 2017). Comparable, consistently operationalized data sets with unambiguous definitions, concepts, and variables are rare. There is a clear lack of such large, high-quality data sets in natural resource management research (Poteete et al. 2010). Open access data are still rare.

Third, unfamiliarity with machine learning methods and the approach in general (Breiman 2001*b*) might lead to hesitation among researchers. Until recently, it was not evident to researchers in natural resource management that machine learning could be of help in modeling. With improved and streamlined software packages available and the success stories from other fields getting more attention, this may change.

If these obstacles are overcome, an increasing spread in methods of machine learning in the field of natural resource management may also lead to a shift in research interest from individual case studies to larger data sets. This development has already been called for (Poteete et al. 2010). This in turn may lead to a different type of data collection and may change the field if data are uniformly collected, structured on the basis of a framework, mainly longitudinal, and extend across several aspects (e.g., social, economic, technical). An example of this is the International Forestry Resources and Institutions database, which has enabled many scientific findings to be achieved (e.g., Andersson and Agrawal 2011, Salk et al. 2014).

Support could also come from increasing performance of computers, which could speed up computations of complex models considerably. Just to name a few possibilities: computing on graphics processing units, using parallel computing software like MPI (message passing interface) on local laptops, or using server clusters in the researcher's scientific institution. If even more computational power is required, high-performance or cloud computing are readily available.

CONCLUSION

The successes of machine learning in many fields of research suggest that their modeling qualities can also be used for analyses in the field of natural resource management. However, this has hardly happened so far—a literature review resulted in only 32 reviewed papers in both more general and topic-specific journals at the interface of machine learning and natural resource management.

I have identified a number of potential reasons why machine learning is rarely applied in natural resource research and have suggested how obstacles in applying machine learning could be overcome. It is not due to the unavailability of suitable data sets, as collections of case studies in meta-analyses (Gutiérrez et al. 2011, Brooks et al. 2012) and research using databases (Tang 1992, Lam 1998, Salk et al. 2014) have proven. I also established that machine learning algorithms are probably well suited to deal with the kind of data that exist in natural resource management.

All algorithms tested (deep and shallow neural networks, and gradient boosting) had a superior explanatory power over traditional linear regressions. However, no algorithm emerged as clearly superior to the others—results were also dependent on the data set and its features. It is important to stress again that models vary widely depending on parameter tuning. In order to identify robust patterns, it is necessary to both run many models and use multiple machine learning algorithms. Only if a pattern is stable across many models and at least two algorithms is there an indication for its existence.

Future research could be based on well-tested architectures. Since all analyses were performed on open access data with open source tools, one such workflow is presented in this article, with the full code provided in Appendix 1. Therefore, adapting such models to one's own data set may consist only of fine-tuning some parameters. For example, this is common practice in image recognition. Furthermore, standard data formats, common definitions of central concepts, and reference data sets and benchmarks for comparing different methods are future central building blocks for advancing natural resource management research.

This brings us to the conclusion that the many different methods of machine learning, not only neural networks, could enrich the methodological toolbox of social-ecological systems analysis. Machine learning methods have proven their worth in many fields, they are both theoretically and practically mature, and there are many easy-to-use software solutions and corresponding introductions and instructions (e.g., the h2o [http://docs.h2o.ai/] or Keras documentation [https://keras.io/]). It is therefore time to apply these methods to questions of natural resource management.

Responses to this article can be read online at:
https://www.ecologyandsociety.org/issues/responses.php/12124

Data Availability:

The data are publicly available on the internet (https://seslibrary.asu.edu/cpr).

LITERATURE CITED

Alpaydin, E. 2010. *Introduction to machine learning.* Second edition. MIT Press, Cambridge, Massachusetts, USA.

Álvarez-Romero, J. G., R. L. Pressey, N. C. Ban, and J. Brodie. 2015. Advancing land-sea conservation planning: integrating modelling of catchments, land-use change, and river plumes to prioritise catchment management and protection. *PLoS ONE* 10 (12):e0145574. https://doi.org/10.1371/journal.pone.0145574

Andersson, K., and A. Agrawal. 2011. Inequalities, institutions, and forest commons. *Global Environmental Change* 21(3):866-875. https://doi.org/10.1016/j.gloenvcha.2011.03.004

Bergstra, J., and Y. Bengio. 2012. Random search for hyper-parameter optimization. *Journal of Machine Learning Research* 13:281-305.

Breiman, L. 2001*a*. Random forests. *Machine Learning* 45 (1):5-32. https://doi.org/10.1023/A:1010933404324

Breiman, L. 2001*b*. Statistical modeling: the two cultures (with comments and a rejoinder by the author). *Statistical Science* 16 (3):199-231. https://doi.org/10.1214/ss/1009213726

Brooks, J. S., K. A. Waylen, and M. Borgerhoff Mulder. 2012. How national context, project design, and local community characteristics influence success in community-based conservation projects. *Proceedings of the National Academy of Sciences of the*

United States of America 109(52):21265-21270. https://doi.org/10.1073/pnas.1207141110

Brown, N., and T. Sandholm. 2019. Superhuman AI for multiplayer poker. *Science* 365(6456):885-890. https://doi.org/10.1126/science.aay2400

Cao, C., S. Dragićević, and S. Li. 2019. Short-term forecasting of land use change using recurrent neural network models. *Sustainability* 11(19):5376. https://doi.org/10.3390/su11195376

Cenek, M., and M. Franklin. 2017. An adaptable agent-based model for guiding multi-species Pacific salmon fisheries management within a SES framework. *Ecological Modelling* 360:132-149. https://doi.org/10.1016/j.ecolmodel.2017.06.024

Ching, T., D. S. Himmelstein, B. K. Beaulieu-Jones, A. A. Kalinin, B. T. Do, G. P. Way, E. Ferrero, P.-M. Agapow, M. Zietz, M. M. Hoffman, et al. 2018. Opportunities and obstacles for deep learning in biology and medicine. *Journal of the Royal Society, Interface* 15(141). https://doi.org/10.1098/rsif.2017.0387

Crespo, G. O., D. C. Dunn, G. Reygondeau, K. Boerder, B. Worm, W. Cheung, D. P. Tittensor, and P. N. Halpin. 2018. The environmental niche of the global high seas pelagic longline fleet. *Science Advances* 4(8):eaat3681. https://doi.org/10.1126/sciadv.aat3681

Elith, J., C. H. Graham, R. P. Anderson, M. Dudík, S. Ferrier, A. Guisan, R. J. Hijmans, F. Huettmann, J. R. Leathwick, A. Lehmann, et al. 2006. Novel methods improve prediction of species' distributions from occurrence data. *Ecography* 29 (2):129-151. https://doi.org/10.1111/j.2006.0906-7590.04596.x

Fernández-Delgado, M., E. Cernadas, S. Barro, and D. Amorim. 2014. Do we need hundreds of classifiers to solve real world classification problems? *Journal of Machine Learning Research* 15(1):3133-3181.

Frey, U. 2018. *Nachhaltige Bewirtschaftung natürlicher Ressourcen: Erfolgsfaktoren in komplexen sozial-ökologischen Systemen.* [1. Auflage] edition. Springer Spektrum, Berlin, Germany. https://doi.org/10.1007/978-3-662-55446-3

Frey, U. J. 2017. A synthesis of key factors for sustainability in social-ecological systems. *Sustainability Science* 12(4):507-519. https://doi.org/10.1007/s11625-016-0395-z

Frey, U. J., and H. Rusch. 2013. Using artificial neural networks for the analysis of social-ecological systems. *Ecology and Society* 18(2):40. https://doi.org/10.5751/ES-05202-180240

Frey, U. J., and H. Rusch. 2014. Modelling ecological success of common pool resource systems using large datasets. *World Development* 59:93-103. https://doi.org/10.1016/j.worlddev.2014.01.034

Girshick, R. 2015. *Fast R-CNN*. [online] URL: http://arxiv.org/pdf/1504.08083v2

Gutiérrez, N. L., R. Hilborn, and O. Defeo. 2011. Leadership, social capital and incentives promote successful fisheries. *Nature* 470(7334):386-389. https://doi.org/10.1038/nature09689

Hochreiter, S., and J. Schmidhuber. 1997. Long short-term memory. *Neural Computation* 9(8):1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

Humphries, G., D. R. Magness, and F. Huettmann, editors. 2018. *Machine learning for ecology and sustainable natural resource management*. Springer International Publishing. https://doi.org/10.1007/978-3-319-96978-7

Intergovernmental Panel on Climate Change (IPCC). 2018. Global warming of 1.5°C. Special report. [online] URL: https://www.ipcc.ch/sr15/

Johnson, M., M. Schuster, Q. V. Le, M. Krikun, Y. Wu, Z. Chen, N. Thorat, F. Viégas, M. Wattenberg, G. Corrado, M. Hughes, and J. Dean. 2017. *Google's multilingual neural machine translation system: enabling zero-shot translation*. https://doi.org/10.1162/tacl_a_00065

Jules Dreyfus-León, M. 1999. Individual-based modelling of fishermen search behaviour with neural networks and reinforcement learning. *Ecological Modelling* 120(2-3):287-297. https://doi.org/10.1016/S0304-3800(99)00109-X

Lam, W. F. 1998. *Governing irrigation systems in Nepal: institutions, infrastructure, and collective action*. Institute for Contemporary Studies, San Francisco.

Le, Q. V., M.'A. Ranzato, R. Monga, M. Devin, K. Chen, G. S. Corrado, J. Dean, and A. Y. Ng. 2012. *Building high-level features using large scale unsupervised learning*. Pages 507-514 *in Proceedings of the 29th International Conference on Machine Learning*, Edinburgh, Scotland, UK, 2012. [online] URL: http://arxiv.org/pdf/1112.6209v5

LeCun, Y., Y. Bengio, and G. Hinton. 2015. Deep learning. *Nature* 521(7553):436-444. https://doi.org/10.1038/nature14539

LeDell, E., N. Gill, S. Aiello, A. Fu, A. Candel, C. Click, T. Kraljevic, T. Nykodym, P. Aboyoun, M. Kurka, et al. 2020. h2o: R interface for the 'H2O' scalable machine learning platform. [online] URL: https://rdrr.io/cran/h2o/

Magierowski, R. H., S. M. Read, S. J. B. Carter, D. M. Warfe, L. S. Cook, E. C. Lefroy, and P. E. Davies. 2015. Inferring landscape-scale land-use impacts on rivers using data from mesocosm experiments and artificial neural networks. *PLoS ONE* 10(3): e0120901. https://doi.org/10.1371/journal.pone.0120901

Mnih, V., K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al. 2015. Human-level control through deep reinforcement learning. *Nature* 518(7540):529-533. https://doi.org/10.1038/nature14236

O'Farrell, S., J. N. Sanchirico, O. Spiegel, M. Depalle, A. C. Haynie, S. A. Murawski, L. Perruso, and A. Strelcheck. 2019. Disturbance modifies payoffs in the explore-exploit trade-off. *Nature Communications* 10(1):3363. https://doi.org/10.1038/s41467-019-11106-y

Ostrom, E. 1990. *Governing the commons: the evolution of institutions for collective action*. Cambridge University Press, Cambridge.

Paruelo, J., and F. Tomasel. 1997. Prediction of functional characteristics of ecosystems: a comparison of artificial neural networks and regression models. *Ecological Modelling* 98 (2-3):173-186. https://doi.org/10.1016/S0304-3800(96)01913-8

Poteete, A. R., M. A. Janssen, and E. Ostrom. 2010. *Working together: collective action, the commons, and multiple methods in practice*. Princeton University Press, Princeton, New Jersey, USA. https://doi.org/10.1515/9781400835157

Salk, C. F., U. Frey, and H. Rusch. 2014. Comparing forests across climates and biomes: qualitative assessments, reference forests and regional intercomparisons. *PLoS ONE* 9(4):e94800. https://doi.org/10.1371/journal.pone.0094800

Saputra, M. H., and H. S. Lee. 2019. Prediction of land use and land cover changes for North Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton. *Sustainability* 11(11):3024. https://doi.org/10.3390/su11113024

Silver, D., J. Schrittwieser, K. Simonyan, I. Antonoglou, A. Huang, A. Guez, T. Hubert, L. Baker, M. Lai, A. Bolton, et al. 2017. Mastering the game of Go without human knowledge. *Nature* 550(7676):354-359. https://doi.org/10.1038/nature24270

Tang, S. Y. 1992. *Institutions and collective actions: self-governance in irrigation*. Institute for Contemporary Studies, San Francisco, California, USA.

Václavik, T., S. Lautenbach, T. Kuemmerle, and R. Seppelt. 2013. Mapping global land system archetypes. *Global Environmental Change* 23(6):1637-1647. https://doi.org/10.1016/j.gloenvcha.2013.09.004

Virtanen, P., R. Gommers, T. E. Oliphant, M. Haberland, T. Reddy, D. Cournapeau, E. Burovski, P. Peterson, W. Weckesser, J. Bright, et al. 2019. *SciPy 1.0—fundamental algorithms for scientific computing in Python*. [online] URL: http://arxiv.org/pdf/1907.10121v1

Appendix 1. Supporting online material

Results of literature search

Table A1. Hits found in the systematic literature search

Journal name	Number of hits for search term: machine learning (ML)	Number of hits for search term: deep learning	Number of hits for search term: neural network	Sum of hits for all search terms	Actual hits after screening; i.e., using ML for natural resource management
Ecology & Society	0	12	1	13	1
International Journal of the Commons	8	16	18	42	0
Sustainability	80	28	137	245	8
Ecological Modeling	219	3	541	763	2
Global Environmental Change	13	4	14	31	1
World Development	10	3	7	20	1
Journal of Environmental Management	103	2	219	324	0
Journal of Cleaner Production	199	75	580	854	0
Environmental Modeling and Software	311	35	500	846	4

PLoS ONE	38+201	66 + 9	653+144	757 + 354	6
Proceedings of the National Academy of Science (PNAS)	137+438	51 +209	188 + 205	376 + 852	0
Proceedings of the Royal Society B	59 + 71	11+ 25	52 +117	122 + 213	2
Nature	13 + 57	3+21	6 + 58	22 + 136	3
Science	38 + 88	1 + 22	18+34	57 + 144	1
Nature Methods	2+26	0+24	2+27	4+77	0
Nature Climate Change	4+17	25+44	1+5	30+66	0
Nature Sustainability	5+13	20+32	0+4	25+49	1

Note*:* The first number in a cell indicates the hits for “social ecological”; the second number indicates “natural resource”.

Overview of all articles using machine learning methods

Table A2. Overview of all articles using machine learning (ML) methods on a topic in natural resource management

NN = artificial neural network; RF = random forest; SVM = support vector machine; RFL = reinforcement learning; ABM = agent-based modeling; BRT = boosted regression trees; MRT = multivariate regression trees

Authors	**Year**	**DOI**	**Topic**	**Type of ML used**	**Journal**
Adisa et al.	2019	https://doi.org/10.3390/su11041145	Predict Maize Production in South Africa	NN	Sustaina-bility
Alvarez-Romero et al.	2015	https://doi.org/10.1371/journal.pone.0145574	Estimate Probability of land use change and river plumes	NN	PLoS ONE
Arima	2016	https://doi.org/10.1371/journal.pone.0152058	Simulate impact of road construction on deforestation and quantify carbon emissions	Bayesian probit land change model	PLoS ONE
Cao et al.	2019	https://doi.org/10.3390/su11195376	Short-Term Forecast of Land Use Change	NN (Recurrent)	Sustaina-bility
Cenek et al.	2017	https://doi.org/10.1016/j.ecolmodel.2017.06.024	Machine learning evolved agent behaviors for	ABM	Ecological modelling

			fishermen		
Crespo et al.	2018	https://doi.org/10.1126/sciadv.aat3681	Classify fishing effort	BRT	Science
De Souza	2018	https://doi.org/10.1016/j.ecolmodel.2018.08.015	Model spatial distribution of deforestation	Maximum Entropy	Ecological modelling
Dreyfus-Leon et al.	1999	https://doi.org/10.1016/S0304-3800(99)00109-X	Model fishermen search behaviour	NN + RFL	Ecological modelling
Ekasingh et al.	2009	https://doi.org/10.1016/j.envsoft.2009.02.015	Predict crop choice	Decision trees	Environ-mental Modeling and Soft-ware
Fan et al.	2018	https://doi.org/10.1371/journal.pone.0198171	Predict the effectiveness of farmland consolidation	SVM	PLoS ONE
Farrell et al.	2019	https://doi.org/10.1038/s41467-019-11106-y	Simulate Exploratory strategies in fishers	RF	Nature
Frey et al.	2014	https://doi.org/10.1016/j.worlddev.2014.01.034	Predict legal security, institutional fairness and other factors in irrigation systems and fisheries	NN	World Develop-ment
Frey et al.	2013	https://doi.org/10.5751/ES-05202-180240	Model success factors in	NN	Ecology & Society

			social-ecological systems		
Gasche et al.	2013	https://doi.org/10.1371/journal.pone.0077566	Predict populations of sole and plaice to control fish harvesting	RF	PLoS ONE
Gutierrez et al.	2011	https://doi.org/10.1038/nature09689	Predict success factors for fisheries	RF	Nature
Jouffray	2019	https://doi.org/10.1098/rspb.2018.2544	Estimate relative influence of human and environmental variables in shaping reef ecosystems	BRT	Proceedings of the Royal Society B
Keane et al.		https://doi.org/10.1038/s41893-019-0458-0	Impact of wildlife management areas on community wealth	Bayesian Network	Nature Sustainability
Li et al.		http://dx.doi.org/10.1016/j.envsoft.2017.07.016	Predict sponge species richness	RF, GLM	Environmental Modeling and Software
Lindkvist	2017	https://doi.org/10.1098/rspb.2016.2762	Estimate performance of different management strategies	RFL	Proceedings of the Royal Society B
Little et al.	2007	https://doi.org/10.1016/j.ecolmodel.2007.01.013	Simulate agents harvesting a renewable	ABM + Bayesian Network	Ecological modelling

			resource		
Magierowski et al.	2015	https://doi.org/10.1371/journal.pone.0120901	Identify land-use drivers of changes in river condition	NN	PLoS ONE
Maldonado et al.	2018	https://doi.org/10.3390/su10114312	Comparison of ML-methods to select socioeconomic indicators in cultural landscapes	Various (NN, RF, Bayesian networks)	Sustaina-bility
Mayfield et al.	2017	http://dx.doi.org/10.1016/j.envsoft.2016.10.006	Predict deforesta-tion	Various (GLM, Bayesian Network, NN, …)	Environ-mental Modeling and Soft-ware
Nguyen et al.	2019	https://doi.org/10.3390/su11133615	Predict soil erosion	RF	Sustaina-bility
Ouyang et al.	2019	https://doi.org/10.3390/su11226416	Identify ecological security patterns	Bayesian Network Machine Learning	Sustaina-bility
Robinson et al.	2020	https://doi.org/10.1016/j.envsoft.2020.104781	Early warning detection of water supply vulnera-bility	Various	Environ-mental Modeling and Soft-ware
Romulo et al.	2018	https://doi.org/10.1038/s41467-018-06538-x	Predict investments in watershed services (IWS) programs	RF	Nature
Saputra et	2019	https://doi.org/10.3390/su11113024	Predict land use and	NN	Sustaina-

al.			land cover changes		bility
Vaclavik et al.	2013	https://doi.org/10.1016/j.gloenvcha.2013.09.004	Classify land system archetypes	NN (Self-organizing map)	Global Environ-mental Change
Woo et al.	2019	https://doi.org/10.3390/su11123397	Measure ecosystem health	RF	Sustaina-bility
Yates et al.	2016	https://doi.org/10.1371/journal.pone.0155634	Model fish species richness and abundance of fish functional groups	BRT and MRT	PLoS ONE
Zhang et al.	2018	https://doi.org/10.3390/su10124600	Predict long-term water system adaptation planning	NN	Sustaina-bility

Description of parameters

Table A3. Description of parameters varied during grid-search for model-optimization for three machine learning algorithms

Method	Parameter	Description	Range varied	Optimum
Generalized linear model	Lambda	controls amount of regularization	0-1	0.4
	Alpha	controls distribution between l1 and l2 penalties	0-1	0
Gradient boosting	Number of trees		50-2.500	1900
	Sample rate	% data sampled (for generalization)	0.4-1.0	0.85
	Max. depth	deepness of tree	5-15	6
	Column sample rate	Number of columns sampled for each split	0.2-0.5	0.32
	Column sample rate per tree	column sampling rates per tree	0.2-0.7	0.44
Shallow neural networks	Epochs	Number of cycles on the training set	30-500	305
	Learning rate	Step size in gradient descent optimization	0.001-0.3	0.15
	Number of hidden neurons	number of neurons in calculating layer	10-500	391
Deep neural networks	Epochs	as above	30-500	403
	Learning rate	as above	0.001-0.3	0.12
	Number of hidden layers	number of calculating layers	2-4	4
	Number of hidden neurons	as above	10-500	492-13-85-111

Variables in Ecological Success

Table A4. Common-pool resouces – Description of variables ecological success consists of

Variable name	Type of data	Short description
loc_ENDDATE	Number	Begin and End date (end)
opl_BEGDATE	Number	Begin and End date (beginning)
Opl_BMARKETS	Likert scale	How are the appropriated units disposed of (beginning)?
opl_CONDITON	Likert scale	Physical condition of the system
opl_EAVERAGE	Number	Average age of the units withdrawn from this resource at the end
opl_EAVERSIZ	Number	Average size of the units withdrawn from this resource at the end
opl_ECONEFF	Likert scale	Short-run Economic Technical Efficiency
opl_effindc	Text	Indicators and means of increasing efficiency
Opl_EMARKETS	Likert scale	How are the appropriated units disposed of (end)?
opl_ENDBLNC	Likert scale	Balance between quantity of units withdrawn and number available (end)
opl_ENDCONDA	Likert scale	How well-maintained is the appropriation resource (end)?
opl_ENDCONDD	Likert scale	How well-maintained is the distribution resource (end)?
opl_ENDCONDP	Likert scale	How well-maintained is the production resource (end)?
opl_ENDDATE	Number	Beginning and ending of the operational level
opl_ENDNTFER	Likert scale	Interference between technology and processes for other resources (end)
opl_ENDPOLL	Likert scale	Problems of pollution (end)
opl_ENDQUAL	Likert scale	Quality of units being withdrawn (end)
opl_ENDRATE1	Number	Volume of withdrawal for fisheries (end)
opl_ENDRATE3	Number	Volume of withdrawal for irrigation (end)

opl_ENDTECHX	Likert scale	Extent of technical externalities (end)
opl_ESEXDEVL	Likert scale	Are the units sexually mature at this size or age (end)?
opl_Evaluate	Text	Brief synopsis of how this system is evaluated (performance)
opl_MTONHA	Number	Metric tons of agricultural product per year per hectare
opl_NEWTECH	Likert scale	Is new technology introduced?
opl_NEWVALUE	Likert scale	External change in exchange value of units appropriated?
opl_ONEMARKT	Likert scale	Do appropriators sell this unit in more than one market?
opl_TAILEND	Likert scale	Adequacy and predictability of water to tailenders
opl_TECHEFF	Likert scale	Technical Effectiveness of water availability
opl_TYPRESUL	Text	Evaluation of results
res_MULTAPPR	Likert scale	Relationship among multiple appropration processes
res_WHENBILT	Number	Date of construction of system
sbg_LGTHUSE	Likert scale	Length of time this subgroup has regularly appropriated
scr_paragrph	Text	Abstract of document being screened

Variable – to – Concept Mapping for the common-pool resources data

Variable Name	Mapped to concept	Variable Name	Mapped to concept
loc_LOCDSCPT	Resource size	ors_Membappr	Participation of users
loc_LOCSIZE	Resource size	ors_Orgparag	Participation of users
opl_endrate2	Resource size	res_DISTHEAD	Participation of users
res_APPRESRC	Resource size	res_DISTOPER	Participation of users
res_BRANCHES	Resource size	res_DISTSAME	Participation of users
res_LENGTH	Resource size	res_HEADOPER	Participation of users
res_LNTHBRCH	Resource size	res_HEADSAME	Participation of users
res_LNTHMAIN	Resource size	res_SECTOR2	Participation of users

res_METHEAD1	Resource size	res_SELEDIST	Participation of users
res_METHEAD2	Resource size	res_SELPROD	Participation of users
res_STOREVOL	Resource size	sbg_MANAGE	Participation of users
res_SURFAREA	Resource size	sbg_PROnurul	Participation of users
res_SYSTAREA	Resource size	scr_TYPE	Participation of users
scr_Slocsize	Resource size	sbg_WITHDRAW	Legal certainty and legitimacy
loc_LOCBOUND	Resource boundaries	loc_ENDDATE	Legal certainty and legitimacy
loc_LOCDSCPT	Resource boundaries	loc_FREQCOMM	Legal certainty and legitimacy
opl_RECORDav	Resource boundaries	loc_jurinam1	Legal certainty and legitimacy
opl_RECORDwi	Resource boundaries	loc_jurinam2	Legal certainty and legitimacy
opl_USERseen	Resource boundaries	loc_locjuris	Legal certainty and legitimacy
res_BOUNDAR2	Resource boundaries	loc_ONECOUNT	Legal certainty and legitimacy
res_BOUNDAR3	Resource boundaries	Opl_BFORMOWN	Legal certainty and legitimacy
res_BOUNDAR4	Resource boundaries	opl_BRIBERY	Legal certainty and legitimacy
res_DESCRIPT	Resource boundaries	opl_duration	Legal certainty and legitimacy
res_DISTAPPR	Resource boundaries	opl_Enddate	Legal certainty and legitimacy
res_OFFNUM	Resource boundaries	opr_DEFpay	Legal certainty and legitimacy
res_PRODAPPR	Resource boundaries	opr_natcolch	Legal certainty and legitimacy
res_PRODDIST	Resource boundaries	opr_regcolch	Legal certainty and legitimacy
res_PRODLOCA	Resource boundaries	opr2_LEGITIM	Legal certainty and legitimacy
loc_LOCDSCPT	Accessibility	ors_Begdate	Legal certainty and legitimacy
opr2_seasonln	Accessibility	ors_Conelect	Legal certainty and legitimacy
res_AVGACCES	Accessibility	ors_Enddate	Legal certainty and legitimacy
res_STEEP	Accessibility	ors_Expother	Legal certainty and legitimacy
sbg_RESIDENT	Accessibility	ors_Expown	Legal certainty and legitimacy
loc_BEGDATE	Ecological success at the beginning	ors_Extremov	Legal certainty and legitimacy
opl_BAVERSIZ	Ecological success at the beginning	ors_Extrep	Legal certainty and legitimacy

opl_BEGBLNC	Ecological success at the beginning	res_DISPUTE	Legal certainty and legitimacy
opl_BEGCONDA	Ecological success at the beginning	res_DONATION	Legal certainty and legitimacy
opl_BEGCONDD	Ecological success at the beginning	res_DONOR	Legal certainty and legitimacy
opl_BEGCONDP	Ecological success at the beginning	sbg_EQIPshar	Legal certainty and legitimacy
opl_BEGNTFER	Ecological success at the beginning	sbg_TRANflow	Legal certainty and legitimacy
opl_BEGPOLL	Ecological success at the beginning	sbg_TRANshar	Legal certainty and legitimacy
opl_BEGQUAL	Ecological success at the beginning	loc_FREQCOMM	Administration
opl_BEGRATE1	Ecological success at the beginning	ors_Execappr	Administration
opl_BEGRATE2	Ecological success at the beginning	ors_Execinc	Administration
opl_BEGRATE3	Ecological success at the beginning	ors_EXECOTHR	Administration
opl_BEGTECHX	Ecological success at the beginning	ors_Execown	Administration
opl_BSEXDEVL	Ecological success at the beginning	ors_Execpaid	Administration
opl_PRIORapp	Ecological success at the beginning	ors_Execper	Administration
opl_reason	Ecological success at the beginning	ors_Offnear	Administration
res_LINED	Ecological success at the beginning	opl_GENinfo	Information
res_ANALUNIT	Manageability	opl_MAPAVAIL	Information
res_CONTROL	Manageability	opl_MAPPROD	Information
res_MICROZON	Manageability	opl_RADIOCOM	Information
res_PREDVAR1	Manageability	opl_RECORDav	Information
res_PREDVAR2	Manageability	opl_RECORDco	Information
res_PREDVAR3	Manageability	opl_RECORDke	Information
res_QUALBETR	Manageability	opl_RECORDla	Information
res_RSRCUNIT	Manageability	opl_RECORDma	Information
res_SECTOR1	Manageability	opl_RECORDmo	Information
res_STOREVOL	Manageability	opl_RECORDph	Information
res_SURFAREA	Manageability	opl_RECORDwi	Information
res_TYPERES	Manageability	opl_UNDERres	Information

res_VAROTIME	Manageability	opr_QUALUNIT	Information
res_VARSPACE	Manageability	opr2_appmonit	Information
res_VARYEAR	Manageability	opr2_appright	Information
res_WATERORI	Manageability	opr2_appwork	Information
sbg_ABSOQUAN	Regeneration of RU	opr2_condres	Information
opl_BAVERAGE	Regeneration of RU	opr2_DEFinf	Information
opl_EXTINCAP	Regeneration of RU	opr2_IOther	Information
res_POTNTIAL	Regeneration of RU	opr2_numunit	Information
sbg_OLSON	Regeneration of RU	opr2_physfact	Information
sbg_SHARCHNG	Regeneration of RU	opr2_qassets	Information
sbg_TECHEXTR	Regeneration of RU	opr2_unitflow	Information
sbg_USERATE1	Regeneration of RU	opr2_WRITTEN	Information
sbg_USErate2	Regeneration of RU	sbg_LITERACY	Information
loc_NUMHOU	Number of actors	opl_aindictc	Characteristics of rules
loc_NUMPOP	Number of actors	opr_CLEAR	Characteristics of rules
opl_BNUMAPP1	Number of actors	opr_DEFAGGR	Characteristics of rules
opl_BNUMAPP2	Number of actors	opr_EQSHARED	Characteristics of rules
opl_BNUMTEM1	Number of actors	opr_FIXNUM	Characteristics of rules
opl_BNUMTEM2	Number of actors	opr_MINSIZE	Characteristics of rules
opl_Enumapp1	Number of actors	opr_NARRANGE	Characteristics of rules
opl_enumapp2	Number of actors	opr_RTRANS2	Characteristics of rules
opl_ENUMTEM1	Number of actors	opr_rulsetsb	Characteristics of rules
opl_ENUMTEM2	Number of actors	opr_RULSETSP	Characteristics of rules
sbg_BNUMUSR1	Number of actors	opr2_A1Other	Characteristics of rules
sbg_BNUMUSR2	Number of actors	opr2_A2Other	Characteristics of rules
sbg_Enumusr1	Number of actors	opr2_aggrrule	Characteristics of rules
sbg_ENUMusr2	Number of actors	opr2_apprtax	Characteristics of rules

sbg_SNUMTEM1	Number of actors	opr2_capinv	Characteristics of rules
sbg_SNUMTEM2	Number of actors	opr2_DEFauth	Characteristics of rules
sbg_TEAMSIZE	Number of actors	opr2_easyund	Characteristics of rules
scr_SNUMapp2	Number of actors	opr2_ELABsubs	Characteristics of rules
opl_CLANID	Group composition	opr2_emerglab	Characteristics of rules
opl_Families	Group composition	opr2_fixorder	Characteristics of rules
opl_RACEID	Group composition	opr2_fixperc	Characteristics of rules
opl_SG1TOSG2	Group composition	opr2_fixtime	Characteristics of rules
opl_SG2TOSG3	Group composition	opr2_FLEXIBLE	Characteristics of rules
opl_SG3TOSG4	Group composition	opr2_freewith	Characteristics of rules
sbg_Sbgpdes	Group composition	opr2_maintlab	Characteristics of rules
sbg_Scaste1	Group composition	opr2_ncycles	Characteristics of rules
sbg_SCLANID1	Group composition	opr2_RULEdur	Characteristics of rules
sbg_Scultvwr	Group composition	opr2_rulsetsa	Characteristics of rules
sbg_Sethid1	Group composition	opr2_sploc	Characteristics of rules
sbg_Sgender1	Group composition	opr2_spseason	Characteristics of rules
sbg_Sgender2	Group composition	ors_Admlevel	Characteristics of rules
sbg_Slang1	Group composition	ors_Ruleclas	Characteristics of rules
sbg_Sothcomm	Group composition	sbg_EQIPshar	Characteristics of rules
sbg_SRACEID1	Group composition	sbg_TRANflow	Characteristics of rules
sbg_Srelid1	Group composition	sbg_TRANshar	Characteristics of rules
opl_BEGTRUST	Social capital	opl_Basis	Fairness
opl_ENDtrust	Social capital	opl_REALoser	Fairness
opl_GENRELtn	Social capital	opl_Realyes	Fairness
opr2_howtran	Social capital	opl_RELequty	Fairness
opr2_LABorg	Social capital	opl_SG1TOSG3	Fairness
ors_Addserv	Social capital	opl_SG1TOSG4	Fairness

ors_Services	Social capital	opl_SG2TOSG4	Fairness
res_WHOBUILT	Social capital	opl_WORSToff	Fairness
sbg_ENTACT	Social capital	opr_UNEQprib	Fairness
sbg_LISTPROB	Social capital	opr_UNEQPUN	Fairness
sbg_OFFSPRNG	Social capital	opr_UNEQrew	Fairness
sbg_Sbgpdes	Social capital	opr2_FAIR	Fairness
sbg_TEAMBASE	Social capital	opr2_UNEQduta	Fairness
sbg_TECHUSED	Social capital	opr2_UNEQpria	Fairness
opl_BRENTDIS	Dependency on resource	ors_Expown	Fairness
opl_ERENTDIS	Dependency on resource	sbg_MAINCONT	Fairness
loc_PERMPOP	Dependency on resource	sbg_SUBvar	Fairness
opl_INSURANC	Dependency on resource	opl_guard	Control
opl_insurdes	Dependency on resource	opl_monpaid	Control
opl_Labor	Dependency on resource	opl_OFFpgrd	Control
opl_labrdays	Dependency on resource	opl_OffpNum	Control
opl_MAINTres	Dependency on resource	opl_PEAKgrd	Control
opl_Penalty	Dependency on resource	opl_PeakNum	Control
opr_PRICESUP	Dependency on resource	opl_RLEVEL	Control
opr_SUMFEES1	Dependency on resource	opl_SELFmon	Control
opr_SUMFEES2	Dependency on resource	opl_USERseen	Control
opr_WAGEUSE	Dependency on resource	opr_ADJOINFD	Control
ors_Fisource	Dependency on resource	ors_Expown	Control
ors_Orgparag	Dependency on resource	res_CONTROL	Control
res_IMPROVED	Dependency on resource	opl_aindictc	Compliance
sbg_ALTSUPLY	Dependency on resource	opl_BRIBERY	Compliance
sbg_ASSETS	Dependency on resource	opl_MONsanct	Compliance
sbg_AVERinc	Dependency on resource	opl_Penalty	Compliance

sbg_AVOIDhrm	Dependency on resource	opl_PHYsanct	Compliance
sbg_ENHANCE	Dependency on resource	opl_SOCsanct	Compliance
sbg_FAMINCDE	Dependency on resource	opl_VARsanct	Compliance
sbg_KPRESURE	Dependency on resource	opr_DEFpay	Compliance
sbg_LONGvar	Dependency on resource	opr_FINES	Compliance
sbg_OWNlabor	Dependency on resource	opr_INCARCER	Compliance
sbg_SUBalt1	Dependency on resource	opr_LOSEentr	Compliance
sbg_SUBALT2	Dependency on resource	opr_SHUNNING	Compliance
sbg_SUBnot	Dependency on resource	opr2_LEGITIM	Compliance
sbg_SUBSIM	Dependency on resource	ors_Enfrule	Compliance
sbg_TEAMCAP	Dependency on resource	ors_Expown	Compliance
opl_OTHRcoop	Dependency on group	sbg_RULEbrak	Compliance
opr_shareorg	Dependency on group	sbg_RULEfoll	Compliance
ors_Fisource	Dependency on group	sbg_RULquanc	Compliance
ors_Orgparag	Dependency on group	sbg_RULtechc	Compliance
sbg_ENTACT	Dependency on group	sbg_RULtimec	Compliance
sbg_OFFSPRNG	Dependency on group	ors_Expown	Conflict management
opl_NONapp	Group boundaries	res_CONFLICT	Conflict management
opl_Numnon1	Group boundaries	sbg_Sbgpdes	Conflict management
opl_NUMnon2	Group boundaries	sbg_VIOLENC1	Conflict management
opl_WELLdefn	Group boundaries	sbg_VIOLENC2	Conflict management
opr_AGE	Group boundaries	opr_LOSEentr	Exclusion
opr_auction	Group boundaries	res_SHARED	Exclusion
opr_BOther	Group boundaries	sbg_EXCLUDED	Exclusion
opr_caste	Group boundaries	opl_BOWNCLOS	Exclusion
opr_CITCOUNT	Group boundaries	opl_EOWNCLOS	Exclusion
opr_citlocal	Group boundaries	opl_BAPCLOSE	Exclusion

opr_CITSUBDI	Group boundaries	opl_EAPCLOSE	Exclusion
opr_CLAN	Group boundaries	sbg_ACCESS	Exclusion
opr_CLASS	Group boundaries	sbg_EXCLUDIN	Exclusion
opr_conusage	Group boundaries	opl_NEWGROUP	Exclusion
opr_DEFbound	Group boundaries	opl_EXTPOLL	Relations
opr_DEMSKILL	Group boundaries	loc_RESCONF	Relations
opr_ELIGIBLE	Group boundaries	opl_Bapclose	Relations
opr_ENTRYFEE	Group boundaries	opl_Bownclos	Relations
opr_ethnic	Group boundaries	opl_commlang	Relations
opr_GENDER	Group boundaries	opl_Cultvwr	Relations
opr_LEVEDUC	Group boundaries	opl_Eapclose	Relations
opr_LICENSE	Group boundaries	opl_Eownclos	Relations
opr_LICLIMIT	Group boundaries	opl_ethncid	Relations
opr_lottery	Group boundaries	opl_Newgroup	Relations
opr_organiza	Group boundaries	opl_NUMsubgp	Relations
opr_OWNAPPRO	Group boundaries	opl_Othrcomm	Relations
opr_ownland	Group boundaries	opl_relanims	Relations
opr_ownright	Group boundaries	opl_sex	Relations
opr_RACE	Group boundaries	opl_socstrat	Relations
opr_RTRANS1	Group boundaries	ors_Expother	Relations
opr_RTRANS2	Group boundaries	ors_Fisource	Relations
opr_seasfee	Group boundaries	res_DESCRIPT	Relations
opr_shareorg	Group boundaries	res_DISPUTE	Relations
opr_shareres	Group boundaries	res_DONATION	Relations
opr_unitsuse	Group boundaries	res_DONOR	Relations
opr_USETECH	Group boundaries	res_IMPROVED	Relations
sbg_Sbgpdes	Group boundaries	res_OFFNUM	Relations

sbg_WELdefin	Group boundaries	res_PARENT	Relations
opl_aindictc	Participation of users	res_PARNAME	Relations
opl_ARENAS	Participation of users	res_WHOBUILT	Relations
opl_ARENfreq	Participation of users	sbg_ACCESS	Relations
opl_NEWOPRUL	Participation of users	sbg_Excludin	Relations
opr_loccolch	Participation of users	sbg_OLSON	Relations
opr2_regcolch	Participation of users	sbg_SUBwhere	Relations
opr_RTRANS2	Participation of users	loc_ECONOLOC	Capabilities to adapt to change
ori_Lev1Act	Participation of users	opl_INSURANC	Capabilities to adapt to change
ori_Lev2Act	Participation of users	opl_insurdes	Capabilities to adapt to change
ori_Lev3Act	Participation of users	opl_reason	Capabilities to adapt to change
ori_OrgType	Participation of users	opr_EXTAID1	Capabilities to adapt to change
ors_Execappr	Participation of users	opr_EXTAID2	Capabilities to adapt to change
ors_Expown	Participation of users	opr_EXTAID3	Capabilities to adapt to change
		sbg_LONGvar	Capabilities to adapt to change
		sbg_SUBvar	Capabilities to adapt to change

LITERATURE CITED

Adisa, O., J. Botai, A. Adeola, A. Hassen, C. Botai, D. Darkey, and E. Tesfamariam. 2019. Application of Artificial Neural Network for Predicting Maize Production in South Africa. *Sustainability* 11(4):1145.

Álvarez-Romero, J. G., R. L. Pressey, N. C. Ban, and J. Brodie. 2015. Advancing Land-Sea Conservation Planning: Integrating Modelling of Catchments, Land-Use Change, and River Plumes to Prioritise Catchment Management and Protection. *PLoS ONE* 10(12):e0145574.

Arima, E. Y. 2016. A Spatial Probit Econometric Model of Land Change: The Case of Infrastructure Development in Western Amazonia, Peru. *PLoS ONE* 11(3):e0152058.

Cao, C., S. Dragićević, and S. Li. 2019. Short-Term Forecasting of Land Use Change Using Recurrent Neural Network Models. *Sustainability* 11(19):5376.

Cenek, M., and M. Franklin. 2017. An adaptable agent-based model for guiding multi-species Pacific salmon fisheries management within a SES framework. *Ecological Modelling* 360:132–149.

Crespo, G. O., D. C. Dunn, G. Reygondeau, K. Boerder, B. Worm, W. Cheung, D. P. Tittensor, and P. N. Halpin. 2018. The environmental niche of the global high seas pelagic longline fleet. *Science advances* 4(8):eaat3681.

Ekasingh, B., and K. Ngamsomsuke. 2009. Searching for simplified farmers' crop choice models for integrated watershed management in Thailand: A data mining approach. *Environmental Modelling & Software* 24(12):1373–1380.

Fan, Y., X. Jin, X. Xiang, Le Gan, X. Yang, Z. Zhang, and Y. Zhou. 2018. Evaluating and predicting the effectiveness of farmland consolidation on improving agricultural productivity in China. *PLoS ONE* 13(6):e0198171.

Frey, U. J., and H. Rusch. 2013. Using Artificial Neural Networks for the Analysis of Social-Ecological Systems. *Ecology and Society* 18(2).

Frey, U. J., and H. Rusch. 2014. Modeling Ecological Success of Common Pool Resource Systems Using Large Datasets. *World Development* 59:93–103.

Gasche, L., S. Mahévas, and P. Marchal. 2013. Supporting fisheries management by means of complex models: Can we point out isles of robustness in a sea of uncertainty? *PLoS ONE* 8(10):e77566.

Gutiérrez, N. L., R. Hilborn, and O. Defeo. 2011. Leadership, social capital and incentives promote successful fisheries. *Nature* 470(7334):386–389.

Jouffray, J.-B., L. M. Wedding, A. V. Norström, M. K. Donovan, G. J. Williams, L. B. Crowder, A. L. Erickson, A. M. Friedlander, N. A. J. Graham, J. M. Gove, C. V. Kappel, J. N. Kittinger, J. Lecky, K. L. L. Oleson, K. A. Selkoe, C. White, I. D. Williams, and M.

Nyström. 2019. Parsing human and biophysical drivers of coral reef regimes. *Proceedings. Biological sciences* 286(1896):20182544.

Jules Dreyfus-León, M. 1999. Individual-based modelling of fishermen search behaviour with neural networks and reinforcement learning. *Ecological Modelling* 120(2-3):287–297.

Keane, A., J. F. Lund, J. Bluwstein, N. D. Burgess, M. R. Nielsen, and K. Homewood. 2020. Impact of Tanzania’s Wildlife Management Areas on household wealth. *Nature Sustainability* 3(3):226–233.

Li, J., B. Alvarez, J. Siwabessy, M. Tran, Z. Huang, R. Przeslawski, L. Radke, F. Howard, and S. Nichol. 2017. Application of random forest, generalised linear model and their hybrid methods with geostatistical techniques to count data: Predicting sponge species richness. *Environmental Modelling & Software* 97:112–129.

Lindkvist, E., Ö. Ekeberg, and J. Norberg. 2017. Strategies for sustainable management of renewable resources during environmental change. *Proceedings. Biological sciences* 284(1850).

Little, L. R., and A. D. McDonald. 2007. Simulations of agents in social networks harvesting a resource. *Ecological Modelling* 204(3-4):379–386.

Magierowski, R. H., S. M. Read, S. J. B. Carter, D. M. Warfe, L. S. Cook, E. C. Lefroy, and P. E. Davies. 2015. Inferring landscape-scale land-use impacts on rivers using data from mesocosm experiments and artificial neural networks. *PLoS ONE* 10(3):e0120901.

Maldonado, A., D. Ramos-López, and P. Aguilera. 2018. A Comparison of Machine-Learning Methods to Select Socioeconomic Indicators in Cultural Landscapes. *Sustainability* 10(11):4312.

Mayfield, H., C. Smith, M. Gallagher, and M. Hockings. 2017. Use of freely available datasets and machine learning methods in predicting deforestation. *Environmental Modelling & Software* 87:17–28.

Nguyen, K. A., W. Chen, B.-S. Lin, U. Seeboonruang, and K. Thomas. 2019. Predicting Sheet and Rill Erosion of Shihmen Reservoir Watershed in Taiwan Using Machine Learning. *Sustainability* 11(13):3615.

O'Farrell, S., J. N. Sanchirico, O. Spiegel, M. Depalle, A. C. Haynie, S. A. Murawski, L. Perruso, and A. Strelcheck. 2019. Disturbance modifies payoffs in the explore-exploit trade-off. *Nature communications* 10(1):3363.

Ouyang, Wang, and Zhu. 2019. Construction of the Ecological Security Pattern of Urban Agglomeration under the Framework of Supply and Demand of Ecosystem Services Using Bayesian Network Machine Learning: Case Study of the Changsha-Zhuzhou-Xiangtan Urban Agglomeration, China. *Sustainability* 11(22):6416.

Robinson, B., J. S. Cohen, and J. D. Herman. 2020. Detecting early warning signals of long-term water supply vulnerability using machine learning. *Environmental Modelling & Software* 131:104781.

Romulo, C. L., S. Posner, S. Cousins, J. Hoyle Fair, D. E. Bennett, H. Huber-Stearns, R. C. Richards, and R. I. McDonald. 2018. Global state and potential scope of investments in watershed services for large cities. *Nature communications* 9(1):4375.

Saputra, M. H., and H. S. Lee. 2019. Prediction of Land Use and Land Cover Changes for North Sumatra, Indonesia, Using an Artificial-Neural-Network-Based Cellular Automaton. *Sustainability* 11(11):3024.

Souza, R. A. de, and P. de Marco. 2018. Improved spatial model for Amazonian deforestation: An empirical assessment and spatial bias analysis. *Ecological Modelling* 387:1–9.

Václavík, T., S. Lautenbach, T. Kuemmerle, and R. Seppelt. 2013. Mapping global land system archetypes. *Global Environmental Change* 23(6):1637–1647.

Woo, S. Y., C. G. Jung, J. W. Lee, and S. J. Kim. 2019. Evaluation of Watershed Scale Aquatic Ecosystem Health by SWAT Modeling and Random Forest Technique. *Sustainability* 11(12):3397.

Yates, K. L., C. Mellin, M. J. Caley, B. T. Radford, and J. J. Meeuwig. 2016. Models of Marine Fish Biodiversity: Assessing Predictors from Three Habitat Classification Schemes. *PLoS ONE* 11(6):e0155634.

Zhang, J., D. Fu, C. Urich, and R. Singh. 2018. Accelerated Exploration for Long-Term Urban Water Infrastructure Planning through Machine Learning. *Sustainability* 10(12):4600.

Code

The following code section shows the full code in R to produce 500 models for deep neural networks with the h2o software package. Data preparation, loading and saving models and results are part of the workflow, but are not specified in detail here, since these are user specific and not part of the core machine learning code.

```
# Load libraries

library(data.table)

library(h2o)

# Load data = user+environment specific => empty



# Initialise H2O

localH2O = h2o.init(nthreads=-1, min_mem_size = "8196M", max_mem_size = "20490M")

# Convert to h2o

h2o_input <- as.h2o(input)

# Split 80:20

splits <- h2o.splitFrame(h2o_input, c(0.80,0))

train <- h2o.assign(splits[[1]], "train")

test <- h2o.assign(splits[[3]], "test")

#####################

# Set Hyperparameter #

#####################
```

```
# Produces architectures

number_architectures <- 20

min_neurons <- 10

max_neurons <- 500

max_nr_layers <- 4

hidden_opts = lapply(1:number_architectures,

function(x) min_neurons + sample(max_neurons, sample(max_nr_layers),

replace=TRUE))

# Select range of learn rates

min_learnrate <- 0.01

max_learnrate <- 0.30

learnrate_stepsize <- 0.005

learn_rate_opts <- seq(min_learnrate,max_learnrate, learnrate_stepsize)

# Select range of epochs

min_epochs <- 50

max_epochs <- 400

epoch_stepsize <- 5

epochs_opts <- seq(min_epochs, max_epochs, epoch_stepsize)

# Cross-validation number of folds

nfolds <- 5

hyper_params = list(

hidden = hidden_opts,
```

```
rate = learn_rate_opts,

epochs = epochs_opts

)

####################

# Set Search Criteria #

####################


maxmodels <- 500


search_criteria = list(

strategy = "RandomDiscrete", # "RandomDiscrete" vs "Cartesian"

max_models = maxmodels

)

###############

# Grid Search #

###############

# Run model grid

dl_grid <- h2o.grid(

algorithm = "deeplearning",

grid_id = "dlgrid",

x = predictors,

y = response,
```

```
training_frame = train,

nfolds = nfolds,

keep_cross_validation_predictions = TRUE,

model_id = "dl_grid",

hyper_params = hyper_params,

search_criteria = search_criteria

)

# Extracting and saving models and model results (user specific => not shown here)

# Shut down the H2O cluster:

h2o.shutdown(prompt = FALSE)
```