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REVIEW ARTICLE

Machine learning in landscape ecological analysis: a review of recent approaches

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Abstract

Context Artificial Intelligence (AI) has rapidly developed over the past several decades. Several related AI approaches, such as Machine Learning (ML), have been applied to research on landscape patterns and ecological processes.

Objectives Our goal was to review the methods of AI, particularly ML, used in studies related to landscape ecology and the main topics addressed. We aimed to assess the trend in the number of ML papers and the methods used therein, and provide a synopsis and prospectus of current use and future applications of ML in landscape ecology.

Methods We conducted a systematic literature search and selected 125 papers for review. These were examined and scored according to multiple criteria regarding methods and topic. We applied quantitative statistical methods, including cluster analysis based on titles, abstracts, and keywords and a non-metric multidimensional scaling based on attributes assigned during the review. We used Random Forests machine learning to describe the differences between identified clusters in terms of the topics and methods they included.

Results The most frequent method found was Random Forests, but it is noteworthy to mention the increasing popularity of tools related to Deep Learning. The topics cover both ecologically oriented issues and the landscape-human interface. There has been a rapid increase in ML and AI methods in landscape ecology research, with Deep Learning and complex multi-step pipeline AI methods emerging in the last several years.

Conclusions The rapid increase in the number of ML papers in landscape ecology research, and the range of

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methods employed in them, suggest explosive growth in application of these methods in landscape ecology. The increase of Deep Learning approaches in the most recent years suggest a major change in analytical paradigms and methodologies that we feel may transform the field and enable analyses of more complex pattern process relationships across vaster data sets than has been possible previously.

Keywords Landscape ecology · Artificial intelligence · Machine learning · Data analysis · Classification · Clustering · Modelling · Prediction

Abbreviations

AI	Artificial intelligence
BRT	Boosted regression trees
CNN	Convolutional neural networks
DT	Decision trees
ES	Expert systems
GAM	Generalized additive models
LoR	Logistic regression
ML	Machine learning
MaxEnt	Maximum entropy
MIR	Model improvement ratio
NMDS	Non-metric multidimensional scaling
NN	Neural networks
RF	Random forests
RNN	Recurrent neural networks
SML	Supervised learning
SVM	Support vector machines
UsML	Unsupervised learning
WoS	Web of Science
XGBoo	XGBoost—gradient boosting machine

Introduction

The last few decades have brought an impressive number of scientific discoveries and novel technologies, ranging from the ubiquitous presence of computers in our everyday lives, genomics, synthetic biology, nanotechnology and advancements in space exploration (Rotolo et al. 2015). Recent technological revolutions, such as the internet of things (Ng and Wakenshaw 2017), virtual reality and other immersive experiences (Klippel et al. 2019) are rapidly transforming human experience, and their development represents both disruptive challenges and exciting opportunities for human society. For example, chatbots powered by artificial intelligence (Androutsopoulou et al. 2019) are now able to engage humans in realistic conversation that is impossible to distinguish from actual interaction with a living human, and deep learning has been able to predict the structures of millions of complex protein molecules (Senior et al. 2020).

A key role in recent explosive technological advances and their impact on human society is played by the field of Artificial Intelligence (AI), considered by John McCarthy as being *"the science and engineering of making intelligent machines"* (Rajaraman 2014). After its formal initiation in 1956, AI slowly emerged over several decades as computer hardware and software evolved in tandem to enable true artificial intelligence. AI has had a sinuous evolution, with ascents and descents, false starts, lost trails and breakthrough moments (Wooldridge 2020). In recent years, stimulated by rapid proliferation of powerful and robust algorithms, as well as the accelerating computational power correlated with the fall of the hardware costs (Mitchell 1999), the field of AI has had exponential growth, with applications in almost every domain of activity, from medicine and health care (Deo 2015), to biology (Geurts et al. 2009), financial modeling (Bahrammirzaee 2010), manufacturing (Tao et al. 2018), engineering (Mishra et al. 2020b) and entertainment (Anderson et al. 2010).

An intelligent system is an entity endowed with particular reasoning capabilities, such as natural language processing, knowledge representation, automated reasoning, machine learning, computer vision, and robotic functionality (Russell and Norvig 2020). Among the functionalities of particular interest for the life sciences and environmental studies is machine learning, namely the ability of computer algorithms and programs to learn from data without being explicitly programmed (Samuel 1959, 2000). The essence of machine learning is an algorithm whose performance improves through experience (Jordan and Mitchell 2015).

The field of Machine Learning (ML) has become a major discipline in itself (Mitchell 1999), and its applications can be found in a multitude of disciplines related to Earth and life sciences, such as remote sensing (Maxwell et al. 2018), geosciences and geological mapping (Cracknell and Reading 2014; Lary et al. 2016), mining biological data (Mahmud et al. 2018), vegetation mapping (Franklin 1995), modeling the species distribution (Stockwell and Peterson 2002), genetics and genomics (Libbrect and Noble 2015) and ecology (Elith et al. 2006). The use of ML techniques is not always a straight road, and many challenges and pitfalls can be encountered (Halilaj et al. 2018). On the other hand, these approaches offer a wide range of opportunities, and they can offer new and fruitful insights (Desjardins-Proulx et al. 2019).

In a nutshell, AI can be regarded as a broad concept which encompasses a range of approaches in which computers use algorithms to learn, create, communicate and predict, while ML can be defined as a specific subset of AI methods (European Commission 2019). In turn, ML provides various approaches, such as supervised learning, unsupervised learning, or reinforcement learning. ML comes with a multitude of tools, techniques, and specific examples (Random Forests, Neural Networks, Deep Learning, clustering), whose learning mechanisms have various degrees of complexity (Joshi 2020).

The use of AI and ML techniques in Landscape Ecology was foreseen when such tools were in their infancy by Zev Naveh, who wrote about *"factual updated information on the present status of the landscapes and their ecodiversity, collected by integrated field surveys and remote sensing, dynamic Intelligent Geographic Information Systems, and other advanced landscape ecological methods"* (Naveh 1994). Important steps were taken in the last several years towards this aim, and there is rapidly increasing interest in developing operational approaches relying on ML that could, for instance, predict the distribution (Evans and Cushman 2009) and abundance of species based on landscape patterns (Chen et al. 2019). Indeed, several premises suggest that AI-based approaches could be of interest in tackling landscape ecological issues. There is an increasing amount of geospatial or biodiversity-related data that waits to be used and interpreted. Indeed, landscape ecology is particularly focused on Big Data analytical issues given that it is the science of the relationships between patterns and processes at multiple scales across space and time, which typically involve many spatially and temporally varying factors which must be measured continuously and interrelated to predict their dynamic interactions (Cushman and Huettmann 2010). ML approaches coupled to powerful cloud-computing platforms enable analysis of datasets that until recently have been intractably large and complex, and could offer solutions for extracting relevant information (Ma et al. 2014) and further translating data into scientific knowledge (Valletta et al. 2017; Shirk et al. in review; Jones et al. in review). Another strength of ML techniques is that they are robust to nonlinear and complex interactions (Silva et al. 2019; Kumar et al. 2021), and they provide sound methods and algorithms for dealing with complex systems under uncertainty and nonstationarity (e.g., Jones et al. in press, Shirk et al. in press), such as is common in ecological systems (Maldonaldo et al. 2018).

This paper aims to review the methods of AI that were applied in landscape ecological and environmental studies, with a focus on ML techniques. The main objective was to understand to what extent ML-related techniques have been used by the landscape ecology community, how they have been applied and how the field is changing. The specific objectives were to identify the most "popular" ML methodologies applied in related studies and to delineate the main topics addressed. Another goal was to assess the trend in the number of ML papers and the methods used.

Methods

Literature search and review protocol

A brief overview of the steps followed during the literature search and review is presented in Fig. 1. The literature search was conducted in December 2020 in WoS (Web of Science). We used the features of the WoS search engine that enabled us to provide groups of words and logical operators. Thus, the search was done according to the topic (which includes title, abstract, author keywords, and keywords plus) for the key-phrases (*"artificial intelligence" OR "machine learning" OR "deep learning" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning"*) *AND* [(*landscape NEAR ecology*) *OR* (*landscape NEAR pattern*) *OR* (*landscape NEAR fragmentation*) *OR* (*landscape NEAR connectivity*) *OR* (*landscape NEAR metric**) *OR* (*landscape NEAR planning*) *OR* (*landscape NEAR change**) *OR* ((*"land use" OR "land cover"*) *NEAR pattern*)].

As one can notice, we considered two groups of key-phrases. The first one referred to the field of AI

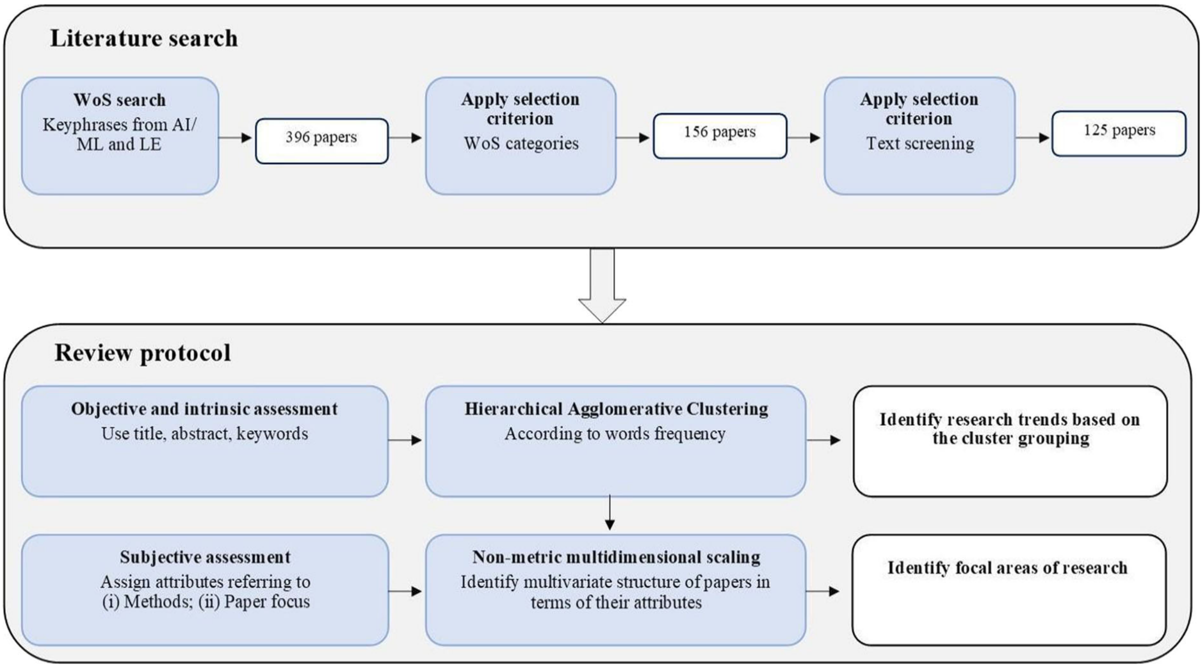

Fig. 1 Workflow chart of the review process. In the upper box the steps of the literature search are represented. In the lower box a synthesis of the review protocol was included

with a particular focus on ML and contained some general phrases such as artificial intelligence, machine learning, deep learning, supervised learning. unsupervised learning, reinforcement learning. We sought to not be overly specific in defining strict application of ML methods, since the goal of this paper was to identify papers that cover the full range of those that mention or use ML approaches to evaluate the scope, trend and focus of ML research in ecology. The second group of key-phrases was directly related to landscape ecology. We referred to major topics of interest, such as patterns, fragmentation, connectivity, metrics and planning, in combination with the key-phrases “landscape”, “land use” and “land cover”.

Our literature search using these criteria produced 396 papers. Two inclusion/exclusion criteria were subsequently applied. Firstly, by using the *Analyze Results* function provided by the WoS search engine, we selected only those papers that corresponded to the following eight WoS categories: *Environmental Sciences, Ecology, Geosciences Multidisciplinary, Environmental Studies, Computer Sciences Interdisciplinary Applications, Biodiversity Conservation, Engineering Environmental, Regional Urban Planning*. This step was performed to reduce papers to those with a clear focus on ecological and landscape science. After the application of this filter we retained 156 papers. Afterwards, each of these papers was reviewed and those that were not directly related to the topic of interest were removed from the list. Finally, 125 papers were selected as the database of the study.

A set of criteria was established for characterizing the papers in the database and several attributes were assigned to each item. Two different tracks were followed in extracting attributes of these papers for further analysis and review. The first one targeted an objective and intrinsic assessment of the attributes of each paper and for achieving this aim we extracted for each paper the abstract, the author keywords and the keywords plus, as provided by the WoS database. The second track aimed to perform a subjective evaluation by characterizing the papers against several criteria. Two types of attributes were recorded. (i) The first group focused on technical and methodological issues. Thus, for each paper we extracted information referring to the ML technique(s) applied in the paper and what it was used for. Besides the method itself and other related information (software used, if technical details regarding the use of the ML technique were provided), we were interested if the ML technique was part of a larger analytical or informatics pipeline and if the paper brought a methodological contribution. (ii) The second group included 27 attributes dealing with the paper focus in relation to landscape ecology. Thus, four of them referred to the characteristics of the study area (non-urban, urban/settlement, mixed/not-available, fine scale). Five attributes were related to landscape structure and patterns (land use/land cover, land use/land cover change, 2D-patterns, 3D-patterns and landforms, roads) while another six dealt with environmental elements (soils, waters, vegetation, agriculture, animals, climate). Another five attributes referred to ecosystems (services/disservices, landscape epidemiology) and to disasters and human-induced hazards (forest fires, storms and pollution). We also evaluated if the paper considered the landscape-human interface, as reflected by five attributes (socio-economic features, cultural landscapes, visual quality, explicit implication of stakeholders and explicitation of potential for decision and management). Finally, we took into account the reference to other "scapes" and whether the paper brought into attention how patterns might affect processes.

Statistical analyses

To identify the main patterns and trends in ML research in landscape ecology and to assess their generality and robustness to different scoring criteria and assessment methods, we conducted two complementary statistical analyses. The first one (cluster analysis) relied on intrinsic information associated with the papers (title, abstract, keywords). The second analysis (non-metric multidimensional scaling) used as input outcomes of the cluster analysis and the attributes that were associated with the papers during the review process.

Clustering analysis

We conducted a hierarchical agglomerative clustering analysis (McGarigal et al. 2000) to group the papers according to the frequency of individual words in their titles, abstracts and keywords. The analysis was intended to objectively identify the hierarchical grouping structure of papers based on the frequency of the words they use. The dataset for the clustering was prepared by turning each word into a dummy variable, and for each paper counting the number of times it occurred in the title, abstract and keywords. The matrix of word frequency across papers was then filtered to remove all words that occurred in only one paper, and all words that were deemed to be not informative (e.g., particles, articles, adverbs). Following the approach in McGarigal et al. (2016) we computed the Bray Curtis distance matrix on the word frequency matrix and then conducted hierarchical clustering using Ward's fusion method in R using the hclust package. We then identified several levels of clustering for further evaluation based on the fusion pattern. We then used random forests (Breiman 2001) to evaluate the relationship between the clusters identified and year of publication and each of the "subjective" attributes recorded for each paper. This enabled us to interpret the clustering, which is based on objective textual analysis of word frequency, in terms of the main characteristics of the paper such as topic, focal issues and methods.

Non-metric multidimensional scaling

We applied a global non-metric multidimensional scaling analysis (NMDS) (Kruskal 1964) to describe the multivariate structure of the sample of papers in terms of their attributes, such as methods and topic, using the subjectively evaluated criteria described above as variables. NMDS is an ordination method, similar to Principal Component Analysis (PCA), which depicts gradients of relatedness among entities in multivariate space, based on a distance matrix (McGarigal et al. 2000). The NMDS analysis is an iterative process that seeks to minimize the overall "stress" of the configuration, by changing the position of objects across a user-defined k-dimensional space (Minchin 1987). We chose this type of analysis because it is best suited for the kind of data that we use in the study, given we are particularly interested in patterns of differences and relatedness among papers. Our data was encoded in discrete binary variables, and NMDS analysis can successfully investigate the structure of it because it uses a rank-based approach for ordination, which is non-metric. Thus, as input, we selected the membership to the two main clusters found in the cluster analysis and the attributes of the papers. We used the R 4.0.3 statistical software (R Core Team 2017) and the package vegan (Oksanen et al. 2016) for performing the analysis. The metaMDS function was run with Bray–Curtis dissimilarity option, two dimensions, and 2000 maximum iterations. The results were scaled using the standard centering, PC rotation, and half change scaling. Finally, we produced a plot of the plane spanned by the first two axes of the NMDS solution.

Results

Methods of ML used in the studies—overview

We first analyzed the most "popular" methods of ML applied in the papers considered in the study (Fig. 2, see also Supplementary Material, Table S1). The most frequent method was Random Forests, used in 51 papers. It was followed by Neural Networks, a technique appearing in 34 papers, among which it is explicitly mentioned that the neural network is a Convolutional Neural Network in 11 papers, while in two papers Recurrent Neural Networks were used. The Support Vector Machine method was also popular, appearing in 19 papers. The supervised techniques appeared in 114 papers, while the unsupervised techniques only in 12 (some papers used a mixture of methods, combining the two approaches). Most methods are data-driven techniques (Rodriguez-Galiano et al. 2015), while some of them (such as Logistic Regression, Generalized Linear Models, Generalized Additive Models) could be also regarded as hypothesis-driven methods (Taverna et al. 2004). Two papers rely on the technique of Reinforcement Learning. Three papers come from a completely different perspective, namely the use of Expert Systems. They are systems (or computer programs) that use expertise, and that are capable of giving advice or to solving problems in a given domain. The approaches of these systems rely on the knowledge of the experts in the field, and it is expected that the solutions are comparable to the ones provided by the humans (Lucas and van der Gaag 1991). The use of knowledge-based approaches can be considered as one of the early trends in ML (Joshi 2020).

Fig. 2 Word cloud with the most frequent ML methods (generated with https://www.jasondavies.com/wordcloud/)

The Random Forests method (Breiman 2001) is widely used in ecology (Brieuc et al. 2018) and in related fields such as remote sensing (Belgiu and Dragut 2016), and our review confirms it is the most commonly used ML method in landscape ecology research. Its wide application likely stems from the fact that it is quite easy to use and is flexible in application to a wide range of data types and questions. It has few assumptions, is non-parametric, and performs well in predicting relationships in the presence of nonlinear and interacting relationships among variables (Rodriguez-Galiano et al. 2012; Kumar et al. 2021). Other advantages of random forest are related to the high accuracy and the ability to determine the relevance of the variables (Cutler et al. 2007).

In recent years, various types of network-based learning have become more well developed and more widely used, and the number of papers applying such techniques has rapidly increased. An Artificial Neural Network, or simply a Neural Network (NN), is a machine learning technique inspired by the human thinking process (Zou et al. 2008). A Neural Network integrates in a complex architecture combining several smaller units (called perceptrons) and its task is to process the input information for predicting the output in the form of classification or regression (Joshi 2020). A Convolutional Neural Network (CNN) is a special case of NN, in which one of the key operations performed is convolution. The convolution is an operation that can detect meaningful features (i.e., characteristics of the data, cf. Géron 2019) while storing fewer parameters (i.e., internal variables of the ML model, cf. Goodfellow et al. 2016; Huettmann et al. 2018). A CNN is suited for grid-type data and therefore this NN model has a wide range of applications for processing imagery data (Albert et al. 2017), in particular geospatial data or satellite imagery (Huang et al. 2018). They were successfully applied for image classification, including more demanding tasks, such as extraction of human-made objects from remote sensing imagery (Alshehhi et al. 2017). The

NN techniques are appealing due to their flexibility in processing large and complex datasets, including those related to vegetation, species, or biodiversity (Christin et al. 2019). The methods relying on such networks are, however, more challenging since innovative network architectures could be necessary (Khan et al. 2020). Overall, the emergence of NN-based methods, the use of more sophisticated architectures with multiple layers and of deep convolutional networks is well correlated with the "deep learning revolution" (Sejnowski 2018) occurring in the last decade (e.g., Senior et al. 2020).

The Support Vector Machines represent a traditional method used both for classification and regression tasks. It has been widely applied successfully in pattern recognition (Burges 1998) and in outlier detection (Ma and Perkins 2003). The method is particularly well suited for the classification of complex relationships but is limited to relatively small or med-size data sets (Géron 2019), and it can generalize well even when the training sample is relatively small (Mountrakis et al. 2011). Major challenges of this method are choosing a suitable kernel (Huang et al. 2002) and the tuning of parameters (Chapelle et al. 2002).

Cluster analysis

Characteristics of the main clusters

The hierarchical clustering applied to our sample papers found distinct structure among ML papers based on the frequency of particular words in their titles, abstracts and keywords. We described three levels of nested hierarchical structure. In the first level, there are two large main clusters describing the main bifurcation in all ML/landscape ecology papers. The first of these clusters is a large group (84 papers) focused on landscape change, land use in a "landscape architecture" context referring to urban and agricultural systems, hydrology, and other geographical topics. This cluster is further split in the next two levels into two and then three subclusters (blue and green boxes in Fig. 3).

The second cluster (41 papers) at the first bifurcation split is stable across the next three levels of splitting of the first cluster—2, 3, and 4-cluster solutions—showing that the cluster is highly distinctive. This is the group of "ecological" papers focusing on habitat, species, ecosystems, and landscapes. It includes papers that predicted landscape change in an ecological context.

There is a clear difference in these two main clusters in terms of date of publication (Supplementary Material, Fig. S1). The first cluster (cluster 1) is very recent, with a median publication date of 2019 and a range from 2017 to 2020. The second cluster (cluster 2) covers a wider range of years with a median of 2014 and a range from 2005 to 2017. This shows that the first cluster represents the most recently emerging work and the second older work in applications of ML in landscape ecology.

A linear discriminant analysis using the year as a predictor of cluster membership was able to classify cluster 1 *versus* cluster 2 with 87% success. Given that year of publication was not a criterion in the clustering, this shows there is a strong distinction between recent and older work based on the words in title, keywords, and abstract. The older cluster (cluster 2) is also very homogeneous, with stability of membership across the four first levels of clustering, while the first newer cluster splits into subclusters, showing the more recent work has diversified and that work in the last three years is much more variable than work in the prior 12.

The first split of the first cluster from level one is into two sub-clusters. The first subcluster (19 papers) word cloud emphasizes Land, Landscape, Water, Forest, Wetland, Land use, Spatial, Urban, Habitat (Supplementary Material, Fig. S2a). The second subcluster (65 papers) focuses more on landscape classification and landscape change mapping, with also emphasis on connectivity (Supplementary Material, Fig. S2b). This split is also highly related to the year of publication (Supplementary Material, Fig. S3). The first subcluster at the 3-cluster strata is exclusively papers published in 2020, while the second includes papers since 2017 with a median of 2019. This shows that among the most recent papers there is a substantial change in the field, as measured by similarity in title, abstract, and keywords between the most recent papers (2020) and the prior few years.

In the 4-cluster strata, the second subcluster from the 3-cluster strata is split into two clusters. The other three clusters remain as they were in the 3-cluster solution. The first subcluster in the 4-cluster strata (38 papers) focuses on landscape, land use, urban, and classification (Supplementary Material, Fig. S4a)

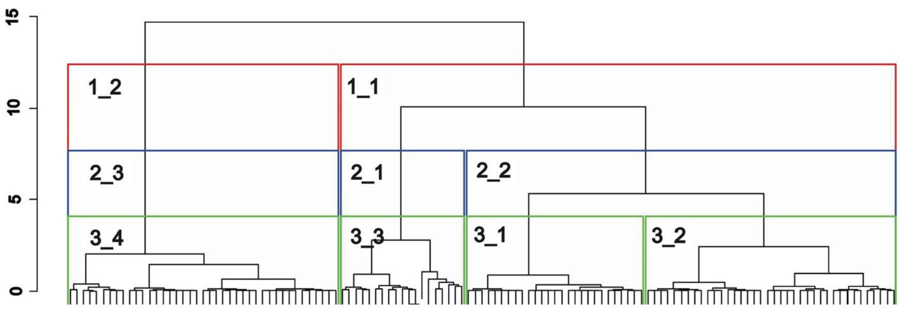

Fig. 3 Hierarchical clustering dendrogram showing colored boxes for the 2, 3, and 4-cluster solutions. The red boxes delineate the first two clusters with the largest differentiation. The blue boxes delineate the three most differentiated clusters. The green boxes delineate the four most differentiated clusters

suggesting a focus on land cover classification and land use prediction (Supplementary Material, Fig. S4b). The second cluster in the 4-cluster strata (27 papers) focuses on landscape change, species ecology, risk modeling. There is a substantial difference in the year of publication among these two subclusters at the 4-cluster strata as well (Supplementary Material, Fig. S5), with the first subcluster consisting largely of 2020 papers and the second largely 2018 papers. The fact that all clusters at each of the first three levels (2, 3, and 4-cluster strata) are highly associated with the year of publication indicates that there is a rapidly changing field of artificial intelligence in landscape ecology such that the main clusters of papers based on differences in titles, abstracts and keywords are highly related to time since publication, indicating rapid and coherent evolution in the field over a very short period of time.

Evaluation of the differences between clusters

We used random forest with the Model Improvement Ratio (MIR; Murphy et al. 2010) to evaluate the differences among clusters in terms of methods used and attributes of the paper. At the first level, the random forest MIR for discriminating among the two major clusters based on methods showed that all methods variables were selected by random forest, but there was a significant difference in their relative importance (Supplementary Material, Fig. S6). The most important variables, in order of decreasing model improvement ratio, for discriminating between cluster 1 and 2 are the methods ES (Expert Systems), SVM (Support Vector Machines), LoR (Logistic Regression), DT (Decision Trees), CNN (Convolutional Neural Networks), GAM (Generalized Additive Models), pipeline (the ML methodology was part of a more complex pipeline), MaxEnt (Maximum Entropy), BRT (Boosted Regression Trees) and NN (Neural Networks). Methods such as ES, SVM, LoR, DT, MaxEnt, GAM were present more frequently in the second cluster. Instead, methods such as NN, CNN, BRT, or the pipeline approach were recorded more frequently in cluster 1 than in cluster 2. The RF (Random Forests) method was present with equal frequency in clusters 1 and 2. The out-of-bag estimate of the error rate was 28%, and the confusion matrix (Supplementary Material, Table S2) hints that in terms of methodology, methods in cluster 1 are not present in cluster 2, but some of the methods in cluster 2 are also present in cluster 1.

In the random forest analysis predicting cluster membership of the first two clusters based on paper attributes, fewer variables were selected (Supplementary Material, Fig. S7). In order of decreasing variable importance based on MIR, the attribute “vegetation” was the most important variable, followed by “3D/landforms/topography”, and “Historical/Archaeology/Cultural/Tourism”. The first two attributes were more commonly a topic arising in the papers of cluster 2, while the latter was more frequently discussed in the papers of the first cluster. The out-of-bag error for predicting class 1 *versus* 2 based on paper attributes was 30.4%, with higher class error for class 2 than class 1 (Supplementary Material, Table S3).

In the random forest MIR modeling to predict membership in cluster 1 *versus* cluster 2 in the three cluster strata (excluding the original cluster 2 from the 2-cluster strata as it is unchanged), all methods variables were selected, with RNN (Recurrent Neural Networks) and SML (Supervised Machine Learning) being by far the most influential, followed by CNN (Convolutional Neural Networks) and UsML (Unsupervised Learning), with the other variables having similar and low effects (Supplementary Material, Fig. S8). More commonly in cluster 1 *versus* cluster 2 are RNN, UsML, CNN, while SML is common to both cluster 1 and 2, but more common in cluster 2, XGBoo (XGBoost—Gradient Boosting Machine) is slightly more common in cluster 2 than 1 and RF (Random Forests) is equally common in both 1 and 2 of the three cluster strata. The out-of-bag error for the discrimination between cluster 1 and 2 in the three cluster tier was 22.62%, with a much higher class error for cluster 1 than 2, meaning that cluster 2 uses methods different than cluster 1, but some of the methods in cluster 1 are also used in cluster 2 (Supplementary Material, Table S4).

For the random forest distinguishing papers in clusters 1 vs 2 of the 3-cluster strata, the MIR indicated that the attributes "2D-patterns", "potential decision/management", "animals", "mixed or N/A (study area)", "vegetation", "water/ice", and "environment/climate" were the retained variables, with "2D-patterns" much more influential than the others (Supplementary Material, Fig. S9). More common for cluster 1 in the three cluster strata were the attributes "vegetation", "animals", "water/ice", "environment/climate", "potential decision/management" while the other two ["2D-patterns", "mixed or N/A (study area)"] were more frequently occurring in the papers in the cluster 2. The out-of-bag error for predicting cluster membership in cluster 1 *versus* 2 in the three cluster strata was 21.43%, with much higher class 1 error than class 2, indicating perfect ability to predict class 2 but extensive misassignment of class 1 as class 2 (Supplementary Material, Table S5).

For the random forest distinguishing papers in cluster 2 *versus* 3 in the 4-cluster tier based on methods, the MIR showed that BRT (Boosted Regression Tree), pipeline (the ML methodology was part of a more complex pipeline), NN (Neural Networks) and SVM (Support Vector Machines) were the most important variables with other variables having similar and low predictive ability (Supplementary Material, Fig. S10). All these four methodological attributes were more common in cluster 2 than 3 in the 4-cluster strata. The out-of-bag error rate for separating clusters 2 and 3 in the 4-cluster strata was 55% with 100% class error for cluster 3, with all observations misassigned to cluster 2 (Supplementary Material, Table S6). The random forest MIR analysis for distinguishing between clusters 2 and 3 for the 4-cluster strata showed that the attributes "LULC" (land use/land cover) and "environment/climate" were the strongest predictors, followed by "design/architecture/perception/visibility", "forest/fires/wildfires", "agriculture" and "animals" (Supplementary Material, Fig. S11). The out-of-bag error for predicting cluster 2 *versus* 3 in the 4-cluster strata was 30.77% with higher class error for cluster 3 than for cluster 2 (Supplementary Material, Table S7). The attribute "LULC" was common in both clusters 2 and 3 of the 4-cluster strata, but more common in cluster 3. The topics "environment/climate", "forest/fires/wildfires", "agriculture", "urban/settlement" were more frequently recorded in cluster 3, while "design/architecture/perception/visibility" was more common in cluster 2 than 3 and the attribute "animals" is equally common in clusters 2 and 3 of the 4-cluster strata.

Non-metric multidimensional scaling

In order to facilitate visualization of how the ML applications match the major interests of the landscape ecological community, we applied the NMDS and produced a plot of the plane spanned by the first two axes. The resulting NMDS plot shows the best configuration found, in which objects ordinated closer to each other are more similar than those further apart. It is worth noticing that NMDS has been successfully applied in a similar study by Simensen et al. (2018), who reviewed methods for landscape characterization. The categories selected were the membership to the first two main clusters provided by the cluster analysis and the attributes of the papers, grouped into landscape structure and patterns, environmental elements, ecosystems, disasters and human-induced hazards, landscape-human interface, reference to other "scapes" and whether the paper brought into attention how patterns might affect processes. The plot (Fig. 4) perfectly reflects the cluster structure obtained from the titles, abstracts, and keywords. In the figure, the points belonging to cluster 1 and cluster 2 in the first main bifurcation were colored with blue and yellow, respectively. We also drew polygons containing the two sets of points for emphasizing the separation that

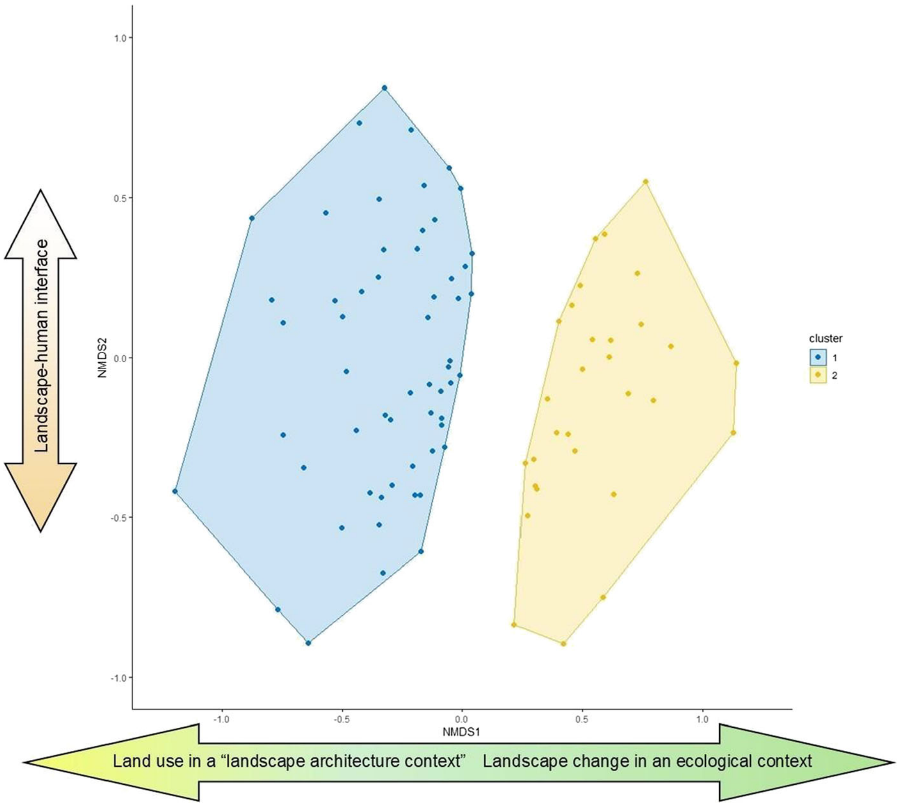

Fig. 4 Plot of the first two axes provided by the NMDS. The points are colored according to their membership to the two large clusters describing the main bifurcation. The convex hulls of the two sets of points were drawn as polygons. The interpretation of the two axes is derived from the topics of the papers in the two clusters

occurs along the first axis. By taking into account the topics of these papers, we concluded that the first axis (Supplementary Material, Fig. S12 and S13) covers both the ecological context (environment, habitat, species) as well as land-use from a “landscape-architectural” perspective, with a focus on how various systems (urban, agricultural) are structured and how they evolve over time. The second axis in the plot could be related to the landscape-human interface, having several important facets: the cultural component (landscape archaeology), the human perception (visual quality and assessment), and the planning perspective (planning, management, and decision). Finally let us mention that there exists a “core” of studies that directly link landscape patterns to processes, but also studies that are tangentially connected to the domain and that envisage related research topics (e.g., climate change).

Discussion

Methods and research topics: evolution and perspectives

There is an increasing number of papers applying ML techniques in landscape ecological studies (Fig. 5). Thus, out of 125 papers, 41 were published in 2020, and 19 papers appeared in 2019. This recent evolution goes along with the exponential growth of the number of papers related to ML (Thessen 2016; Kong et al. 2020). Our analyses indicated that not only the number of papers increased but also the methods became more diversified and the more complex approaches were brought into implementation in the last several years. The papers in the database cover a wide range of topics. Most of them are related to land cover/land use classification and their change, including particular types such as forest. There is also a relatively large number of studies dealing with species and their

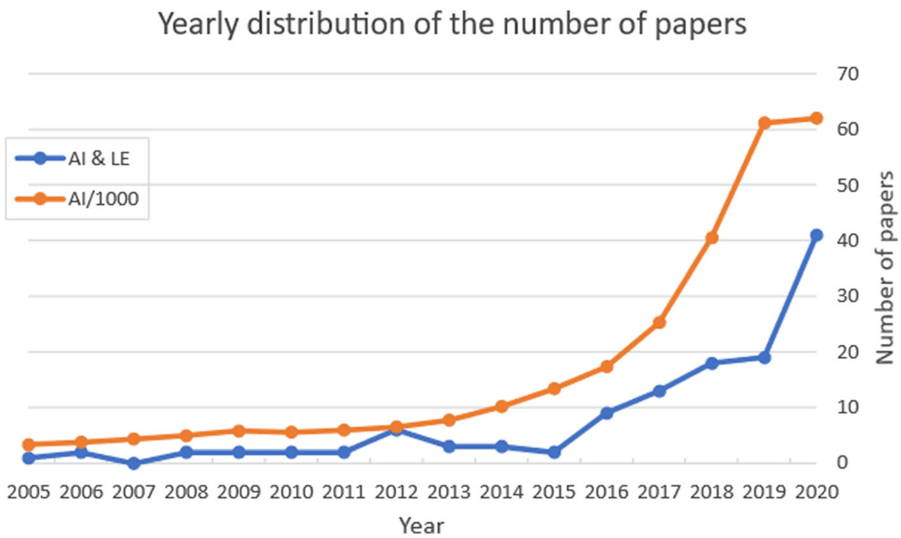

Fig. 5 Evolution over time of the number of papers in WoS dealing with AI (blue, the actual number is divided by 1000) and with applications of AI in landscape ecological studies (blue, the papers that represent the database of the study)

distribution. A few papers also bring to attention socio-economic and cultural topics.

No unique hierarchy of methods

When addressing a landscape ecological problem with ML methods, the natural question is whether there is an a priori approach that is best suited to that problem. Several papers considered in this study provided some insights by comparing several methods in various contexts. The main finding of those comparative papers was that there is no unique hierarchy of models and no method that is universally superior to others. By no unique hierarchy of methods we mean that the ML methods in use have a range of nonexclusive and overlapping characteristics such that they cannot be distinctly grouped into nested groups based on their characteristics, and different methods can provide complementary information and vary in their utility depending on the structure of the data and question being addressed. This statement goes along with the "No Free Lunch Theorem" claiming that there is no single optimal solution for all types of problems (Wolpert and Macready 1997). It can be deduced from studies that reported comparable outcomes (Maldonaldo et al. 2018; Debanshi and Pal 2020b), especially when working across scales (Dronova et al. 2012), that combinations of methods (Saeidi et al. 2017; Xu et al. 2019a) or ensemble models may perform better (Folmer et al. 2016). The difficulty of performing a comparison resides not only in the nature of the problem addressed but also in the fact that the outcomes may depend on the dataset and the model tuning (Chen et al. 2019). On the other hand, several studies provided clear hints that specific methods perform better in a given context. Some of them indicated that the Random Forests technique outperforms other methods such as logistic regression for prediction of forest loss (Cushman et al. 2017) and species distribution modeling (Cushman and Wasserman 2018; Kumar et al. 2021), Generalized Additive Models and Support Vector Regressions in predicting soil nutrients (Jeong et al. 2017), other ensemble models in crop classification (Shukla et al. 2018) or than Decision Trees in a problem dealing with nest-site selection (Frommhold et al. 2019). In modeling stream impairment, Random Forests were found easier to train and robust to overfitting compared to Boosted Regression Trees (Giri et al. 2019). Other studies indicated that Support Vector Machines performed better than Random Forests in the classification of livestock activities (Eikelboom et al. 2020) or that Support Vector Machines were more appropriate than Decision Trees and Random Forests for land cover classification (Keshtkar et al. 2017).

In some analyses, two methods had comparable performances: for instance Support Vector Machines and Random Forests (Liu et al. 2020) or Random

Forests and Neural Networks (Lidberg et al. 2020). The Deep Learning techniques offer an opportunity to select some internal characteristics, such as a specific architecture or particular activation functions. Thus, various models were compared when assessing the forest landscape visual quality (Jahani and Rayegani 2020), or a new convolutional neural network was proposed for processing bioacoustic data (Chen et al. 2020).

A possible optimal approach would be to use a specific method for each given task in multi-stage analyses. For instance, one could combine unsupervised and supervised methods, such as Bastille-Rousseau and Wittemyer (2021) for characterizing movescapes or Qian et al. (2020) for dynamic land use simulations. Another solution is to use complementary methods. For example, Chen et al. (2019) proposed combined approaches, in which some techniques (Neural Networks, Support Vector Machines or k-Nearest Neighbors) were applied for prediction, while Random Forests were used for assessing the relative importance of various predictors. In the studies relying on satellite imagery, a (complex) preprocessing step could be required. It is worth mentioning that, especially in recent papers, the ML methods were part of a more complex workflow and were aggregated with other techniques.

Software tools supporting ML methods

Most studies used R as the main software tool for data training, model validation, and testing. We also found some analyses that relied on Python, Matlab, or other specific tools (e.g., Weka or TreeNet). Indeed, the R software environment plays a crucial role in ecological analyses, and its popularity is reflected by the large number of papers in which a suitable package of R was used (more than 50 papers out of 125). On the other hand, in the programming community, the Python language has become very popular and is now widely used in Machine Learning and Data Science. It provides an increasing number of scientific libraries and application programming interfaces that could be of interest when applying ML techniques in landscape ecological issues. Another advantage of Python follows on the fact that it was adopted by the geospatial community, and it can be used as a scripting language in various geographical information systems (GIS). From this perspective, developing tools or instruments that apply ML techniques in the framework provided by a GIS could make such approaches available to a broader community of researchers and practitioners.

Focal areas of application of the ML methods

The 125 papers we analyzed were identified by applying the search protocol a wide range of topics. Methods stemming from AI/ML were used for various and, in several cases, intertwined tasks, such as mapping, classification or feature extraction, modeling/association, prediction, simulation. Indeed, the applications of ML techniques can cover a wide range of topics (e.g., Olden et al. 2008, Huettmann et al. 2018, Gutzwiller and Chaudhary 2020).

Mapping

This task refers to an approach in which the final outcome of the ML pipeline is a map or a geo-spatial representation. In the 18 papers dealing with mapping, the most commonly used method was Random Forests (a share of 50%), followed by Neural Networks and Support Vector Machines (both with a share of 16.67%). The mapping approaches focused on land use/land cover (Huang et al. 2018; Storie and Henry 2018; Yin et al. 2018; Pavri and Farrell 2020), land and vegetation cover (Evans and Cushman 2009; Samarkhanov et al. 2019), or land cover change (Keshtkar et al. 2017), by applying ML methods to satellite imagery. More focused applications dealt with vegetation communities (Helmer et al. 2008; Henderson et al. 2014; Mishra et al. 2020a). The vegetation studies were also directed towards ecological niches (Drake et al. 2006) and plant functional types (Dronova et al. 2012) or referred to croplands and agricultural fields (Debats et al. 2016; Dimov et al. 2017). Environmental issues were also tackled in relationship with mapping insect distribution (Davies et al. 2020) or aboveground Carbon density (Ashner et al. 2016). More oriented towards the interface between landscape and humans was the mapping of aesthetic suitability (Saeidi et al. 2017).

Classification and feature extraction

In the classification and feature extraction tasks, the aim is to use the ML algorithms for grouping the variables of interest in classes (pre-determined or not), or to identify in the input data certain characteristics. Random Forests and Support Vector Machines were the most used methods used for classification and feature extraction (with a share of 42.42% and 24.24%, respectively). In addition, Convolutional Neural Networks were more frequently used in classification and feature extraction papers (15.15%) than other categories we evaluated. ML approaches to classification were frequently applied in studies that measured and characterized the landscape structure. Determining land use/land cover is the most common goal, but not the only topic of interest in ML applications to classification and feature extraction. The papers cover topics ranging from class delineation (Chapman et al. 2010; Griffiths et al. 2010; Vanderhaegen and Canters 2017; Ross et al. 2018; Xu et al. 2019b; Athukorala and Murayama 2020) to the identification of complex boundaries between urban and non-urban land (Feng et al. 2016). Other landscape elements considered were soils (Chang et al. 2011; Lidberg et al. 2020), landforms, topographic and morphological features (Ginau et al. 2020; Shumack et al. 2020). Topics related to vegetation dealt with species identification (Horning et al. 2020) or detection of growth (Jones et al. 2014; Bayr and Puschmann 2019) and covered a wide range of scales, from the classification of vegetation communities at a very high resolution (Greaves et al. 2019), to large-area crop classification (Shukla et al. 2018). Special attention was paid to issues related to animals. Thus, we found topics such as recognition of bird species based on acoustic information (Ross et al. 2018), identification of tropical bat calls (Chen et al. 2020), establishing predictor variables for nest-site selection (Frommhold et al. 2019), classification of activities (Eikelboom et al. 2020), analysis of functional connectivity for wildlife species (Day et al. 2020) and extraction of movescapes (Bastille-Rousseau and Wittemyer 2021). A few papers brought into attention topics oriented towards the human perspective, such as extraction of semantic features from photographs (Payntar et al. 2021), dating test data of cultural layers (Olsoy et al. 2020), and assessment of landscape aesthetic value (Kerebel et al. 2019). It is worth noticing that some papers brought to attention holistic approaches, aiming to sort places according to their characteristics (Aschwanden 2016) or to compute the similarity between landscapes (Jasiewicz et al. 2014).

Modeling

Almost half of the papers in the database dealt with modeling. This refers to establishing a relationship between different entities or existing data, such that certain variables or objects of interest (one or more) are characterized by using appropriate descriptors. The latter are expected to be more accessible, while the former are supposed to be meaningful, but difficult to be assessed or measured directly. The top three modeling approaches, with a share of 31.59%, 15.79%, and 14.04%, respectively, include Random Forests, Neural Networks, and Boosted Regression Trees. The statistics showed that the range of methods used for modeling was varied. For instance, the Expert Systems and the Reinforcement Learning were found as methodologies applied only for modeling problems.

In this group of papers, there was a large focus on modeling land cover and land use, and their changes (Bone and Dragicevic 2009; Huang et al. 2009; Papadimitriou, 2012; Shafizadeh-Moghadam et al. 2017; Pourmohammadi et al. 2019; Pazur et al. 2020). Some papers addressed specific topics such as estimating the probability of occurrence of specific land cover types (Zheng et al. 2020), modeling landscape dynamics with expert-systems (Pechanec et al. 2012; Pechanec 2013), modeling the land use suitability (Djuric et al. 2013), identifying drivers of resilience (Lucash et al. 2019) or the potential of change (Cushman et al. 2017; Zubair et al. 2017). Applications of ML in landscape modeling often focused on identifying drivers of change in relationship to various explanatory variables (Wang et al. 2016; Christensen and Arsanjani 2020) or determining the mechanisms of land use change (Levers et al. 2018). Moreover, ML methods are often employed to establish links between land use patterns and environmental quality (Zhang et al. 2020) or to investigate relations with structural patterns (Arndt et al. 2019). Models of environmental elements in our review focused on environmental predictors (Jeong et al. 2017), geomorphic processes (Perignon et al. 2020), acoustic-environmental connections (Mullet et al. 2016), stream impairment (Giri et al. 2019), and water richness in relationship to CH4 emissions (Debanshi and Pal 2020a) or wetland habitat suitability (Debanshi and Pal 2020b). Of particular interest is the modeling of phenomena that might impact the environment: drivers of fire occurrence (van Beusekom et al. 2018; Miranda et al. 2020), assessing the impact of 3D urban architecture (Sun et al. 2020) or landscape composition (Osborne and Alvares-Sanches 2019) on the land surface temperature, effect of land-use distribution on particulate matter pollution (Li et al. 2020), monitoring of environmental degradation (Rachmawan et al. 2018).

Vegetation-related topics often focused on identification of species (Balzotti et al. 2020) and prediction of species distributions (Altartouri et al. 2015), with a focus on biodiversity hotspots (Werneck et al. 2012). The determinants of the vegetation structure were studied in different contexts, such as identifying relationships between landscape phenology and flowering (Huete et al. 2019), determining explanatory variables for vegetation features (Barbosa and Asner 2017), assessing the influence of environmental factors on foliar distribution patterns (Balzotti and Asner 2018) and investigating the potential impact of large-scale climate phenomena (El Niño-Southern Oscillation) on crops (Lu et al. 2017). Vegetation dynamics research employing ML methods often focused on modeling forest loss at multiple scales (Cushman et al. 2017) or predicting drivers of vegetation change (Aiba et al. 2016; Balzotti et al. 2020; Vidal-Macua et al. 2020). Animals, livestock, and wildlife species were studied in a multitude of contexts. The most frequent focal topics were predicting species distributions (Magness et al. 2008; Giles et al. 2016; Kampicher and Sierdsema 2018; Bounas et al. 2020; Thomson et al. 2020), species richness (Hopton and Mayer 2006), habitat suitability (Folmer et al. 2016; Singh et al. 2017; Wagner et al. 2020), including co-occurrence of wildlife and livestock species (Hassell et al. 2021). Other papers focused on specific autecological topics for particular species or systems (e.g., how birds are attracted by nocturnal lights (McLaren et al. 2018). Genetic approaches, referring to genetic structure (Hether and Hoffman 2012) and gene flow (Fountain-Jones et al. 2017) were also tackled with ML methods.

Despite a large number of modeling papers, the human-related component was only infrequently addressed. We found topics such as the relationship between socio-economy and cultural landscapes (Maldonaldo et al. 2018), the relevance of photographs in the context of cultural ecosystems (Karasov et al. 2020), assessment of the visual quality of forest landscapes (Jahani and Rayegani 2020) as well as models of pedestrian reactions in an urban environment (Naderi and Raman 2005).

Prediction and simulations

This task refers to applying ML techniques for establishing relationships between various variables, but, unlike the modeling, the focus is on simulated data. The most frequently used methods in prediction and simulation were Random Forests (59.10%) and Neural Networks (22.73%). Ecological predictions with ML methods frequently focused on especially species occurrence and distribution (Liu et al. 2011; Donnelly et al. 2017; Curry et al. 2018; Baltensperger and Joly 2019; Chen et al. 2019) and habitats (Kennedy et al. 2015), including prediction of wildlife damage to agricultural resources (Sommerfeld et al. 2021) or the spread of zoonotic-related diseases (Brock et al. 2019). Simulations or predictions also frequently focused on land use/land cover changes (Shade and Kremer 2019; Xu et al. 2019b; Qian et al. 2020), with particular attention to agricultural issues (Moriondo et al. 2013; Yaramasu et al. 2020), biomass (Hudak et al. 2012) or soil organic carbon stocks (Hounkpatin et al. 2018). Particular attention was paid to water systems (Konapala et al. 2020; Talukdar and Pal 2020) and their behavior in the context of disturbances (Fox and Magoulick 2019). Prediction of disasters refers to determining fire probabilities (Gray et al. 2018). Recent contributions refer to the socio-ecological context in relation to a bundle of ecosystem services (Lorilla et al. 2020) and the simulation of stakeholder involvement (Tian et al. 2020).

Overall, the usefulness of ML methods resides in their abilities to process a large amount of data and to address nonlinearities and more complex dependencies (Elith et al. 2008; Kumar et al. 2021). Thus, by using supervised ML techniques, one can model/predict how one or more variables of interest depend on numerical descriptors which are at hand. The nature of the model depends on the ML technique itself (parametric, non-parametric) and on the datatype used (classification or regression-type model).

Opportunities and challenges

When tackling a specific problem with AI or ML methods (Fig. 6), the first question that might arise

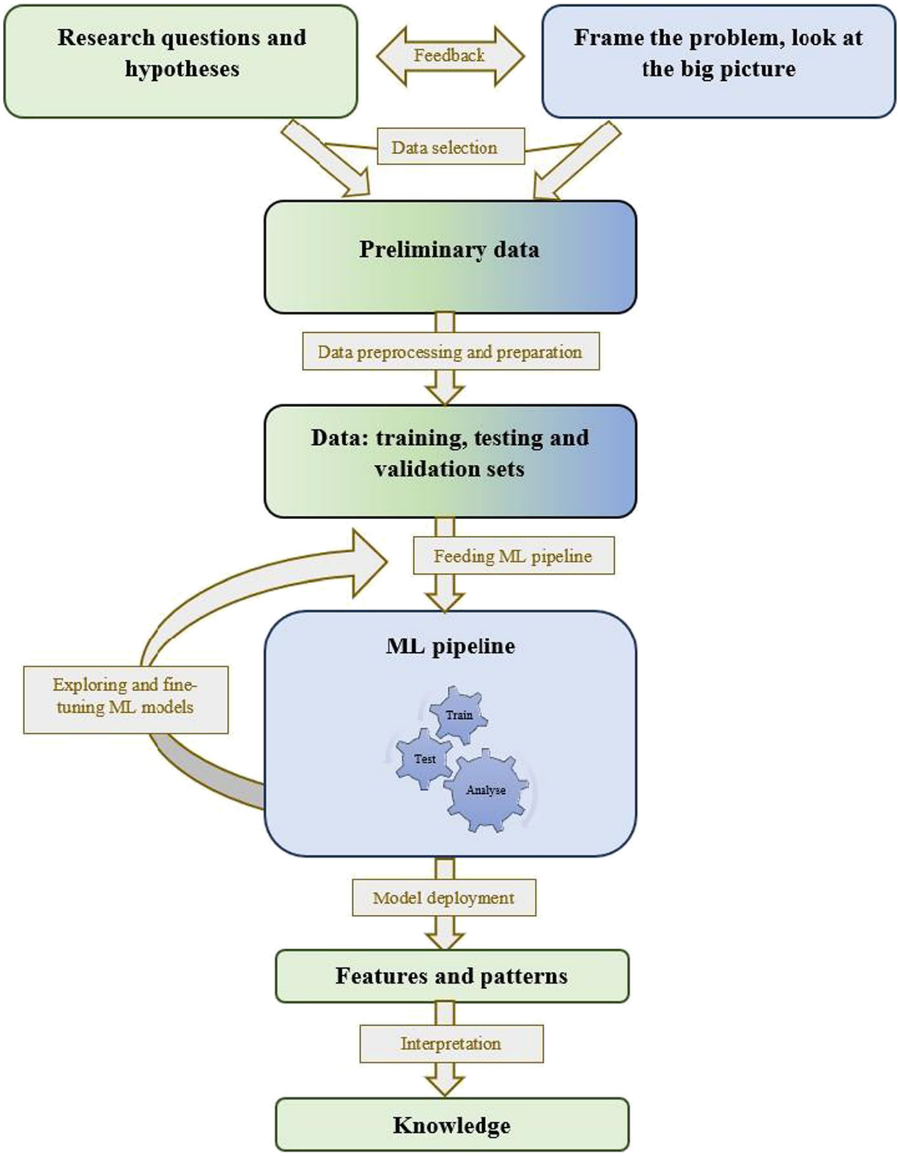

Fig. 6 Relationship and intertwining between landscape ecological analysis (green) and machine learning (blue). The data analysis flow is adapted from Willcock et al. 2018, Fayyad et al. 1996. The machine learning approaches are adapted from Géron 2019, Hapke and Nelson 2020, and Zhou 2018

would be whether there is an "appropriate" method to address it. The comparisons provided by several studies hinted that it is hard to provide a clear and unequivocal answer. Some evaluations have suggested partial hierarchies and those studies might be useful when attempting to select a methodology. On the other hand, it is important to correctly apply, follow and describe the ML workflow (Géron 2019). A minimal protocol is necessary, such as indicating the underlying hypothesis for choosing a specific method, detailing the number of features, the size of the training/validation/test datasets, indicating the measure of the generalization error, providing technical details on the architecture in the case of the Neural Networks (number of layers, activation functions used, etc.). Several shortcomings may appear and need to be considered, such as variables overlooked, patterns that might influence the classification, and technical issues that might decrease the accuracy (Brovelli et al. 2008). From this point of view, presenting key technical details instead of generalities regarding the approaches proposed has the advantage of the study replicability. Furthermore, since ML essentially relies on data, the applications of its associated techniques in landscape ecological problems could provide valuable information and examples for ML or Data Science researchers. This highlights once again the need to carefully apply the specific ML rules and protocols. The communication between scientists and ML developers (Liu et al. 2018) would be beneficial and could open interdisciplinary perspectives. Moreover, the black boxes of the ML techniques (Lucas 2020) could become this way more translucent.

The areas of applicability could be extended by taking over and adapting emerging methodologies and approaches from related fields, such as Computer Vision (Grys et al. 2017), Geometric Deep Learning (Bronstein et al. 2017), or Data Science (Farley et al. 2018). Indeed, the first two research directions take into account the spatial representation of data (2D and 3D, respectively), while the latter one could propose suitable approaches for handling the data. When referring to data, the availability of public repositories could be indeed useful for comparing various models, or even for getting samples for training and testing the models. More and more resources for geo-spatial data or biodiversity data can be freely accessed. The diversification of the methodologies and the extension of the datasets could be fruitful in studying topics that are of interest, such as the effect of sample size (Luan et al. 2020), the impact of scale (Dronova et al. 2012), and proceeding to multiscale analyses (Cushman et al. 2017).

ML techniques are very powerful, but one needs to appropriately balance them with the capacity of human interpretation. This is due, for instance, to some limitations of the ML (and, more generally, AI) approaches (Hernandez-Orallo 2017), often related to their sensitivity to training which can affect their generalizability and predictive power. It is therefore desirable to use expert knowledge and to have extensive human supervision and interpretation when interpreting and, if applicable, when implementing the outcomes of automated-driven analyses (Portelli 2020). Moreover, the needs and perspectives of practitioners need to be taken into account, otherwise such studies would remain at theoretical level (Mac Aodha et al. 2014). This calls for tools that are easy to use and interpret, and which have a user-friendly interface that can be easily integrated into a GIS. Another solution could be provided by the participatory approaches (Fagerholm et al. 2012). The participation of various stakeholders could be beneficial in both directions: more data could be gained for feeding various algorithms and, in turn, the practitioners could benefit from new insights useful for management, planning, or decision.

Last but not least, an important topic when discussing AI applications refers to the need for ethics. This issue receives increasing attention at the international level, and regulations or methodologies are provided by various organisms (e.g., COE 2020). Such rules are applicable when using automated ML techniques, but especially when designing more intelligent systems that can take decisions by themselves or in collaboration with a human.

Conclusions

This paper provides an objective review and quantitative analysis of the current uses, trends and future directions of AI applications to landscape ecological studies, with a focus on ML techniques. A cluster analysis based on the titles, abstracts, and keywords of 125 papers indicated that there is a clear distinction between recent and older work in terms of the methods, topics and scope of research. In particular, this hinted at a rapid evolution in the field over a very short time period and to a high degree of synchronization between landscape ecological studies and the ML trends more broadly across fields. Specifically, in landscape ecology, ML techniques such as random forests were adopted early and continue to be widely used, while methods related to neural networks and Deep Learning are now rapidly being advanced and increasingly used.

The majority of the papers in the database we evaluated used ML techniques. Among them, the most common was Random Forests and this method was rather uniformly used over time. In recent years, other methods, related to the development of Deep Learning, were tested and adopted by the community. This suggests a broadening of the methodological base of ML and AI as applied in landscape ecology and a rapid increase in technical sophistication. We believe this foreshadows rapid expansion of landscape ecology research facilitated by ML and AI to address complex, multiscale, temporally dynamic interactions that previously have been intractable due to complexity and data volume.

We found that there is no unique and universal method to address a given task. ML techniques rely on data, and a rigorous application of the ML rules and best practices is necessary. Moreover, it is worth noting that recently the applications of the ML and AI methods in landscape ecology have increasingly been incorporated into more complex workflows which provide streamlined pipelines for multi-stage analysis. This suggests that the applications of ML and, by extrapolation, of AI in landscape ecology are becoming rapidly more diverse, sophisticated and powerful in addressing increasingly demanding problems.

ML methods have been used for a multitude of tasks, such as mapping, classification/feature extraction, modeling, prediction, and simulation. We found that land use and land cover mapping is the topic which first began to employ AI and ML methods, and now they are increasingly used in a much wider range of topics, such as landscape architecture, scenario optimization, complex systems research and ecological forecasting. The cluster analysis, combined with the non-metric multidimensional scaling indicated a complex and evolving trajectory of ML and AI applications in landscape ecology, with recent proliferation of both the number and the range of methods and topics employed. The topics of the papers covered ecologically oriented issues, oriented towards the ecological context and, especially more recent work, focusing on landscape change and land use in a "landscape architecture" context. Another important dimension of the studies was related to the landscape-human interface.

Overall, there is an increasing and sustained interest in applying AI and especially ML techniques in landscape ecological problems. Increased communication with the members of the ML community would open new perspectives for interdisciplinary approaches. Moreover, extending the collaboration with practitioners and stakeholders could contribute to a democratization of these approaches and could lead to novel applications.

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