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Posted Date: 24 July 2023

doi: 10.20944/preprints202307.1573.v1

Keywords: Artificial intelligence; environmental impact assessment; strategic environmental assessment; biodiversity; digitalisation

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AI Will Change EA Practice—But Are We Ready for It? A Call for Discussion Based on Developments in Collecting and Processing Biodiversity Data

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Abstract: The opportunities and potential of Artificial Intelligence (AI) in Environmental Assessment (EA) are often mentioned. However, do we in the EA field understand the implications of what is happening in other biological sciences, and are we preparing for the changes that are coming? This interdisciplinary letter focuses on AI-driven developments in biodiversity data and analysis as a starting point for stimulating discussion about what AI means in practice for the field of EA. We highlight implications for training, transformation of practice and decision making as first steps in a research agenda.

Keywords: Artificial Intelligence; digitalisation; environmental assessment; biodiversity; monitoring; machine learning; data collection; data processing; data analysis; species; habitats

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Introduction

Digitalisation involves the introduction and integration of digital technologies and systems into various sectors of society, including environmental assessment (EA). A growing number of sciences and disciplines related to EA, such as urban and conservation planning and management, as well as wildlife ecology and biodiversity monitoring, are already widely influenced by the application of advanced digital technologies (Tabak et al. 2019, Schneider et al. 2021, Jetz et al. 2022, Yap et al. 2022, Xing et al. 2022, Salman & Hasar 2023, Wild et al. 2023, Tuia et al. 2022). In biological science in particular, the application of artificial intelligence (AI) combined with affordable hardware and advancing technologies is claimed to improve predictions of ecosystem dynamics by providing access to affordable long-term, high-resolution and large-scale data, while offering great potential for efficient monitoring of global biodiversity (Lahoz-Monfort & Magrath 2021). Authors such as Tuia et al. (2022), Besson et al. (2022), and others discuss the multiple possibilities of machine learning and deep learning for monitoring wildlife and adapting conservation efforts accordingly. Loss of biodiversity is considered to be the most significant global environmental threat, along with climate change, so the development of best practices for accounting for biodiversity in EA is particularly relevant (Figueiredo Gallardo et al. 2022). We discuss below how these new ways of collecting data, processing large amounts of data, and analysing data much more quickly are likely to contribute to change in EA - looking for instance at learning loops from monitoring to scoping and providing baseline data for EA (González Del Campo and Gazolla 2020, Fonseca 2022).

Combining the discussion of novel technological advances in biological science, as one of the fields with a rapid expansion in scientific exploration on AI, with the way we deal with the assessment of different environmental issues in EA, we look at opportunities and concerns attributed to the application of novel advanced digital approaches. Looking at scientific literature on EA, we find that several papers mention potential of the exploration of artificial intelligence (Fonseca 2022, Bice & Fischer 2020, Bond & Dusík 2019, Banhalmi-Zakar et al. 2018). These studies remain at an abstract level. Some papers and reports provide overviews of first pilot projects and applications of AI in EA (Curmally et al. 2022, Fothergill & Murphy 2021, Ravn-Bøss et al. 2021) or of AI use in EA research (Scott et al. 2018, Ulibarri et al. 2019, Scott et al. 2020, Hileman et al. 2021). Current discussion among EA practitioners e.g., in the IAIA working group on Principles for the Use of Artificial Intelligence, reflects concerns about the use of AI. Empirical research analysing EA practice such as Uhlhorn et al. (2023) show the low awareness of technological advances and the controversial perception of these applications in some parts of the EA community. Thus, a need to explore and discuss the implications of AI for EA practice seems highly necessary.

In what follows, we, as an interdisciplinary team, discuss the implications of AI for EA, linking advances from the perspective of biological sciences to environmental assessment. We explore an exemplary thematic area focusing on species and biodiversity related aspects of digitalization to discuss potential opportunities and concerns of AI in EA. The discussion is based on the following guiding questions: How will the application of AI potentially change our EA practices? Could AI help overcome key challenges within EA?

Looking specifically at the linkage between novel developments in biological science and environmental assessment, we deal with the following sub-questions: Is AI a game changer for the consideration and preservation of biodiversity through diverse opportunities for monitoring? Could AI application consequently introduce real learning-loops as outlined and envisaged by EA scientists for decades and particularly needed in times of complex planning conditions and uncertainties deriving e.g., from climate change?

In the following we discuss key topics related to AI application against an interdisciplinary background of literature, adding experience from planning practice working with AI in species monitoring and highlight further demand for research. We follow the structure along the process of data collection/ capture, data processing, data analysis and interpretation as well as data storage and sharing, connecting these novel opportunities to EA procedural steps.

Automated Digital Biodiversity Data Collection, Processing and Management in EA – What Is Possible?

Data collection is still often a limiting factor to both the quality and effectiveness of EA but also impacting the follow-up process, which should contribute to learning and adapting measures, in case they fail to unfold their potential to mitigate harm to environmental resources (González del Campo 2012, Cillier et al. 2022). While other fields such as air quality monitoring have a longer tradition in automated data collection to be used for EA (Hejlová et al. 2013, Kumar et al. 2015), biodiversity data is to the majority collected on site by experienced experts during environmental impact assessment (EIA) processes.

Looking at biological science we see that several automated technologies have significantly improved the collection of biodiversity data, providing richer and more detailed information on species distribution, abundance, and ecological processes. So far, most of the biodiversity monitoring in the context of EA still relies on taxa specific experts and time intensive field work. Advances in technologies such as acoustic sensors, unmanned aerial vehicles (UAVs) and camera traps now allow for rapid, non-invasive, and high-resolution collection of sound and image data. Three developments lead to this large-scale adoption of sensor networks in biodiversity monitoring (Speaker et al. 2022):

1) Consumer market driven development of UAVs and camera traps led to significantly reduced costs and highly intuitive operation (Glover-Kapfer et al. 2019).
2) The open sourcing of sensor hardware and software like the Audiomoth audio recorder reduced upfront costs and allowed for a fast community-driven development of monitoring tools (Hill et al. 2019).
3) The large amount of raw data produced by these sensor networks can be processed and stored using consumer IT hardware and available AI pipelines (Feng et al. 2019).

Consequently, according to authors such as Farley et al. (2018), ecology has entered the realm of big data due to developments in sensor technology and decreasing costs. Advances in sensor

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 24 July 2023 doi:10.20944/preprints202307.1573.v1

technologies play a critical role in biodiversity data collection by enabling real-time, broader, and continuous monitoring of various environmental parameters (Lahoz-Monfort & Magrath 2021). Visual monitoring technologies are widely used for automated monitoring of wildlife, for example autonomously triggered cameras (Oliveri et al. 2023). Remote sensing technologies, including satellite imagery and UAV sensors are automated tools that capture data on land cover, vegetation dynamics, and habitat characteristics (Chabot & Bird 2015, Hodgson et al. 2018, Lyons et al. 2019). Advances in molecular analysis have led to the application of automated eDNA collection devices, such as autonomous samplers or filtration systems, which, when combined with DNA barcoding and metabarcoding, provide valuable information about species, particularly in aquatic systems (Bagley et al. 2019, Hendricks et al. 2023). Studies using terrestrial passive acoustic monitoring have become increasingly important (Ross et al. 2023).

Experts in the field identify two major developments in the near future: 1) Multi-Modal AI pipelines combine different sensors outputs like picture and sound to allow for even more robust automatic species recognition (van Klink et al. 2022). 2) Edge computing[1] moves the analysis onto the sensor itself. The smart camera trap automatically takes a picture and processes the species recognition on the device without any internet connection (Kays & Wikelski 2023). Only pictures of target species are saved. This reduces the amount of raw data generated and complies with the EU General Data Protection Regulation as no human pictures get saved.

To sum up the emergence of open-source monitoring equipment allows for large scale applications outside of academic research (Hill et al. 2018). In the following we discuss implications for EA practice.

How Might Smarter Data Collection, Processing and Open Data Repositories Impact EA Practices?

Besides methodological and procedural limitations, resources (financial and expert availability) are often limiting the availability and quality of baseline data used for scoping, the zero variant, monitoring, and consequently also the availability of data for future impact assessment, and tiering across planning levels (Gachechiladze-Bozhesku & Fischer 2012, Dias et al. 2022).

Particularly EA monitoring practice for species and habitat conditions is to a large extent limited by its dependence on highly trained experts conducting fieldwork. According to Stroud et al. (2022) the future workforce, however, will not have the required taxonomic training needed to complete this task. Novel technological advances could significantly reduce the need for human centred data collection. Experience in AI based data compilation shows, however, also the essential role of experts to explore the full potential of AI and arrive at an accuracy and validity needed for commissioning purposes.

This links the discussion to the responsibility of data collection, comparability, and quality control. While in other disciplines, data is often standardised by national and international law and collected by official authorities nation-wide or at least for federal states, the collection of biodiversity and species data is still diversely managed. Managing and maintaining sensor networks and aggregating produced raw data remains a labour-intensive task and requires specific skills. It seems obvious, that discussion about origin of data but also about responsibilities for data collection (and storage – see section below) is needed. Related questions refer to quality control of the systematic data collection and the prevention of manipulation. Processing large amounts of data into meaningful ecological measurements remains a challenging task to automate. Raw data needs to be run through reproducible pipelines and always must be accompanied by standardised open metadata formats like the Darwin Core Standard (Wieczorek et al. 2012). Open metadata is needed to find, use, and understand data sets from wide array of monitoring schemes. Using well documented metadata is

[1] „Edge computing: a distributed computing paradigm that brings computation to the 'edge' of a network by processing and analyzing data in real-time on the same device that collects the data, rather than sending all data to a centralized location for processing." (Kays et al.& Wikelski 2023, 2)

essential for correctly interpreting the data and carrying out meaningful comparisons with data sets from different origins. In the context of EA, this is especially important, when automated workflows must be accepted by authorities and the public. In this context, applicants and users need to assure the comparability of data collected. To provide an example, the picture of a lynx is useless, when information on where and how the camera trap was placed, for how long, and with what settings, is missing.

Additionally, we need to negotiate which institutions could be responsible for systematic data collection, and who is responsible to cover the costs. Normally, data collection related to EIAs is managed by the project developer, and the project developer is also responsible for monitoring, if the project permit includes this condition. While novel options arise through continuous data collection, the questions of responsibilities and resources as well as knowledge and capabilities reach a new turning point.

Opportunities arise not only through minor impacts on wildlife behaviour during observation periods (with less disturbance through human presence in the field), but also the continuous availability of raw data showcasing real-life situations - which could provide substantial facts during the assessment of significant environmental impacts. Additional observation in the field on site might nevertheless be needed, particularly under certain circumstances, e.g., when it comes to abundance (population size at the specific location, percentages in comparison with the total population across Europe). Right now, AI is already strong in species detection but still quite weak in abundance estimates. There is, for instance, ongoing development towards individual song recognition of single individuals, and also spatial sound analysis that makes it possible to do more precise abundance estimates. So far, however, these capacities would not suffice for the population estimates needed for EA, but might change soon. Consequently, constant update between disciplines and evolution of AI application would be relevant to keep authorities and consultants updated on technological developments and opportunities. In this context, questions of human capacities and options for training arise.

Finally, the discussion on data collection, capacities, and resources related to it, is directly linked also to the questions on data accessibility and storage. So far, accessibility of data from past EA processes is challenging, as latest research on digitalisation in EA practice shows (Lyhne et al. 2022, Geissler et al. 2022, Uhlhorn et al. 2023, Garigliotti et al. 2023). While even the collection of environmental reports is partly hindered by legal circumstances and the lack of digital platforms, the sharing of raw data is so far very scarcely applied – although it would be very useful for tiering between planning levels and learning as originally intended by monitoring. Aggregating raw data and processed data in open and general repositories would allow agencies and companies in EA to share the cost related to the collection and data processing effort and lead to more trust in data quality and workflows. Databases like the Global Biodiversity Information Facility (GBIF) are already established and are actively developed. Questions now relate to the abilities and willingness of the EA community as well as adequacy of framing conditions such as legal standards, which might enhance or on the contrary impede digital data sharing and usage.

Data Analysis and Interpretation Supported by AI – What Is Possible?

AI techniques such as image recognition and natural language processing can automate the identification of key features in ecological datasets. This includes the automatic recognition of species, habitats, land cover types, and other relevant attributes, saving significant time and effort in comparison. While data collection is primarily related to automated collection of data, the real impact of AI becomes relevant during the analysis of large amounts of data. The raw data - after collection as outlined in the section before - then has to be processed by AI algorithms. Latest studies in biological science show that AI offers promising solutions to address biodiversity challenges by automatically identifying and classifying species (Besson et al. 2022, Wägele et al. 2022).

Most applied systems to date are based on deep learning, a type of machine learning based on multilayer artificial neural networks. More specifically, they are supervised deep learning algorithms that need high quality labelled data to learn to identify species from raw data (Borowiec et al. 2022).

Human experts must go through large datasets and correctly identify the species on this training data. The quality of the final model output mainly depends on the quality and balance of this training data. The used training data must be documented and openly published. With biodiversity data this also means that one needs the permission by the data owners (species experts, companies, agencies) to use and publish their data accordingly (Urbano et al. 2021). This also means that data of protected species might have to be restricted and the exact locations must be obscured in order to prevent negative impacts by disturbance or even destruction (Bubnicki et al. 2023). From first application contexts and studies we see that these are very critical discussion points, which deserve future studies to examine the perspectives of diverse groups of actors e.g., authorities, consultants, and NGOs to map concerns and at the same time invite for consideration of opportunities.

AI supported Workflow – What Are Benefits and Challenges?

Critical voices refer to the traceability of the AI supported analysis and its suitability as a basis for legal commissioning processes (e.g. according to nature protection laws) and monitoring according to EU Directives such as the EIA Directive, the Habitats Directive, or the Water Framework Directive. Implementing and trusting AI workflows often suffers from the black box effect. Recent developments strive for a more explainable AI (xAI). xAI uses frameworks that help humans to understand and interpret predictions made by AI models. This also allows for identifying unbalanced training data that might lead to biased model performance towards species with frequent observations. Just like the data standards for the raw data, we need data standards to document the used AI models, software version, and used settings. A trained AI model in the context of biodiversity monitoring is never finished but must be continuously improved. Using the example of detecting invasive species, this means that there is no training data for a species in a biogeographically region in which it has not yet appeared. Each novel detection must then be labelled, and the model be retrained in this new context. AI models need constant development and cannot be frozen in time to be included in a regulation or guidance standard. This will require a balance between standardizing the approaches (as required in legal commissioning and assessment processes) and ensuring enough flexibility for the models to be further developed and adopted to novel conditions.

Questions for future responsibilities and capacities of the diverse actors involved in EA come up. While consultancies may fear that some of their core resources are less needed, we see that engagement by EA actors in these new technological advancements is absolutely necessary. Trained experts are needed to advance the algorithms and provide quality control, but who is to be responsible for the training? To this aim, an understanding of the digital advancement is essential as well as skills of species identification itself. Today, a combination of both with knowledge of EA processes is rare. Therefore, we emphasise questions of preparedness among EA actors and the necessity of interdisciplinary knowledge transfer and open discussion.

Conclusions and Suggestions for Further Research

Our exploration of the rapid development of digital technologies within biodiversity shows a wide array of potentials for smarter and faster data collection, data analysis and generation of reports. As one of a series of environmental factors mentioned in the SEA and EIA Directives, biodiversity appears a frontrunner of the impressive technological developments that will be further expanding in the years to come. New digital technologies are also increasingly applied within water, climate, and other environmental fields, and the scope of applications seems very wide across the concept of environment in the directives.

AI and digital technologies seem to constitute parts of the solution to current criticisms to EA practice. As for biodiversity in EA, digital technologies may meet criticisms around data collection, data analysis, and monitoring (Geißler & Jiricka Pürrer, 2023) and thus potentially contribute to shorten permit processes and speed up green transition (as e.g., called for by the European Commission, 2022). It may ease efficient monitoring of global biodiversity and improve predictions of ecosystem dynamics (Lahoz-Monfort & Magrath 2021) and at the same time facilitate learning and tiering as originally intended in EA. However, digital technologies and AI may also induce new problems, lead to new practices, and the rapid technological development means that we as an EA community need to step up on identifying and discussing implications along with the potentials. In order to balance between exploring advances and their advantages and at the same time maintain quality control for EA standards, we additionally need new funding for two big challenges: 1) We need publically funded and run data repositories driven by interdisciplinary teams for high quality training and reference data sets (examples would be www.xeno-cantho.org or the www.macaulaylibrary.org). 2) We need additional funding to keep our "traditional" monitoring schemes running in parallel with new digital monitoring tools in order to keep our monitoring time series valid (or establish them further) and transform them into the future. This might then allow also the transformation of EA while at the same time trying to assure quality and traceability of decisions taken.

Overall, AI seems to be the technology with the largest potential for changing the current ways of conducting environmental assessments. Like development in other disciplines (Eloundou et al. 2023), AI will undoubtedly change EA practice. The questions are how, and whether we are ready for it?

Based on the previous sections, we surmise that AI technologies within few years will result in a wider set of baseline data at lower cost and higher speed than currently. This will likely A) improve our knowledge about species populations and their status, B) qualify significance determinations, and C) potentially speed up planning processes. But it will likely also lead to D) a transformation of the classical biologists towards digital dexterity as field studies become automated, E) 'technification' of discussions around accuracy and validity of collected data and thereby quality of EA, F) challenges to public acceptance and legitimacy of EA as the technification may be perceived as black box to parts of the public, G) need for new training of competences among actors involved in EA to exert quality control and interpret data, and H) require update of legislation and guidance related to data management.

Our key message is that the digital development is not a task for a few specialists, but for many of us involved in EA. The digital development is not just another change in these years, but a transformation that will affect us all. We thus need, as a field of related actors, to raise attention to digital developments and the discussion on how we want digital technologies to support us, rather than wait and see how we will be changed by the technological development. The current work on principles for use of AI in IA amongst members of the IAIA is a good example of the discussions we need to engage in, but the current extent of discussions is far from sufficient for us to make a proactive stance on digitalisation and AI.

We therefore suggest an outline of topics for a research agenda on digital technologies in IA. They go beyond the field of biodiversity and include interrelated topics that necessitate interdisciplinary and potentially transdisciplinary research:

i. Standardization of EA: Digitalisation of EA on the one hand requires standardization and uniformity of terminologies and content of EA reports. How much do we as a field accept to standardise across actors and contexts and how to standardise smoothly? When is standardization needed on the other hand, to ensure comparability of AI based interpretation of data and under which circumstances is this possible at all?
ii. A new role for specialists in EA: As data collection is increasingly automatised, specialists are less needed for observations on sites. Rather, specialists should ensure the right technology application for the purpose, quality check data collection, and interpret the data. Do we foresee another collaboration, another dialogue, and another type of specialists in EA processes?
iii. Changing responsibilities and roles: How will roles and institutional responsibilities in EA practice be affected by the new distribution of tasks between public bodies and private developers in curating and managing data for the description of the current state, the consideration of alternatives and particularly the monitoring of unexpected impacts and the effectiveness of measures? How to implement the polluter pays principle accordingly if new knowledge and capacity building is needed to work with new digital approaches?
iv. Understanding of digital technologies: How much understanding would be needed to ensure quality and validity of results? We already apply modelling software in EA processes, but how

to compensate implications in case lack of understanding of technologies becomes more evident with increased degree and sophistication of digitalisation? Who in EA processes should understand and be able to explain technical aspects?

v. Acceptance and legitimacy of decision-making: Increased technification of processes risks being perceived as "black boxes", especially in applications of AI. How do we as a field position ourselves in terms of transparency? And what does technification and black boxes mean for authorities' acceptance and public acceptance of EA results? What does it mean in terms of power (im)balances? Under what circumstances do we risk gambling with the legitimacy of EA in the digital transformation?

vi. Effectiveness of EA: How will digital technologies influence substantive, normative and transformative effectiveness? Will we be able to use digital technologies as a lever to increase effectiveness, or do we risk losing focus on effectiveness in our own transformation?

vii. Motivation and identity: As the role of specialists, writers and coordinators of EA processes will change, how does it affect our ideals of best practices, our identity, and our motivations? Would roles of software programmers or accountants be more prominent in EA practice, and would they need understanding of sustainability and democracy?

viii. Training and competences: The rapid digital development means a need for rapidly changing skills. How do we ensure that we as a field have sufficiently updated skills? How should we change educational programs to ensure the upcoming need for competences?

ix. Learning and coping with uncertainty: Will these novel developments provide a real option to introduce and continuously apply adaptive monitoring as recommended by several scholars for dealing with uncertainty?

x. Research and Evaluating IA: How will this change research and evaluation of IA and also of procedural steps under researched so far such as monitoring and quality related questions? What are new research designs supported by AI? Which risks but also chances for EA research quality, transparency, replicability, and legitimacy does this entail?

We see a need for future studies emerging from an interdisciplinary perspective into AI application at diverse steps of the EA process to examine its opportunities throughout scoping, assessment of alternatives, assessment of significant environmental impacts, and monitoring. At the same time, these studies need to profoundly investigate risks and susceptibility to manipulation.

With this letter we invite everyone to refine, criticise, challenge, and/or act on the suggested topics. This letter has complemented other initiatives that in total have scratched the surface of the changes that we will face in the years to come, and we hope for increased discussions on how to navigate and act, for reflections across actors in EA on what digital technologies means for us as a field and for practices, and for increased number of proactive decisions on what and how do deal with digital technologies.

Acknowledgements: The experiences and challenges identified in this letter is in part gained from a number of research projects, including the project "International trends in EIA and SEA research and practice 2.0" funded by the German Environmental Agency (UBA) (grant agreement number, FKZ 3721131010) and the DREAMS project funded by the Innovation Fund Denmark (Innovationsfonden) (grant agreement number, 0177- 00021B DREAMS).

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