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Perspective

Artificial Intelligence Meets Citizen Science to Supercharge Ecological Monitoring

Eva C. McClure,[1,*] Michael Sievers,[1] Christopher J. Brown,[2] Christina A. Buelow,[1] Ellen M. Ditria,[1] Matthew A. Hayes,[1] Ryan M. Pearson,[1] Vivitskaia J.D. Tulloch,[3] Richard K.F. Unsworth,[4] and Rod M. Connolly[1]
[1]Australian Rivers Institute – Coast and Estuaries, School of Environment and Science, Griffith University, Gold Coast, QLD 4222, Australia
[2]Australian Rivers Institute – Coast and Estuaries, School of Environment and Science, Griffith University, Nathan, QLD 4111, Australia
[3]Department of Forest and Conservation Science, University of British Columbia, Vancouver, BC, Canada
[4]Seagrass Ecosystem Research Group, College of Science, Swansea University, Swansea SA2 8PP, UK
*Correspondence: e.mcclure@griffith.edu.au
https://doi.org/10.1016/j.patter.2020.100109

THE BIGGER PICTURE Citizen science and artificial intelligence (AI) are often used in isolation for ecological monitoring, but their integration likely has emergent benefits for management and scientific inquiry. We explore the complementarity of citizen science and AI for ecological monitoring, highlighting key opportunities and challenges. We show that strategic integration of citizen science and AI can improve outcomes for conservation activities. For example, coupling the public engagement benefits of citizen science with the advanced analytical capabilities of AI can increase multi-stakeholder accord on issues of public and scientific interest. Furthermore, both techniques speed up data collection and processing compared with conventional scientific techniques, suggesting that their integration can fast-track monitoring and conservation actions. We present key project attributes that will assist project managers in prioritizing the resources needed to implement citizen science, AI, or preferably both.

1 2 3 4 5 Mainstream: Data science output is well understood and (nearly) universally adopted

SUMMARY

The development and uptake of citizen science and artificial intelligence (AI) techniques for ecological monitoring is increasing rapidly. Citizen science and AI allow scientists to create and process larger volumes of data than possible with conventional methods. However, managers of large ecological monitoring projects have little guidance on whether citizen science, AI, or both, best suit their resource capacity and objectives. To highlight the benefits of integrating the two techniques and guide future implementation by managers, we explore the opportunities, challenges, and complementarities of using citizen science and AI for ecological monitoring. We identify project attributes to consider when implementing these techniques and suggest that financial resources, engagement, participant training, technical expertise, and subject charisma and identification are important project considerations. Ultimately, we highlight that integration can supercharge outcomes for ecological monitoring, enhancing cost-efficiency, accuracy, and multi-sector engagement.

INTRODUCTION

Ecological monitoring is integral to environmental management and biological conservation.[1,2] As the need for monitoring species, habitats, and ecosystems increases, so too do the ways in which scientists and managers involve personnel and technology to collect, process, and analyze both samples and data.[3,4] With advances in technology and the capacity to collect big datasets, data processing has become a major bottleneck that requires novel solutions.[5–7] Under such circumstances, scientists and managers may need access to large teams of people with the skills to enable data processing, or computer intelligence may need to fill this gap. Both techniques are already being utilized, by harnessing people power through citizen science and computing power through artificial intelligence (AI).

Citizen science can be described as scientific projects that engage volunteers of varying levels of expertise with scientific research.[8] These projects produce data usable by a range of stakeholders,[9] across spatial and temporal scales that are otherwise unachievable by conventional means.[6,10,11] AI refers, broadly, to technology and software with the capacity to perform tasks otherwise requiring human intelligence.[12] There is a gradient of complexity in AI available, from weak AI approaches, such as smartphone applications that assist human-led data

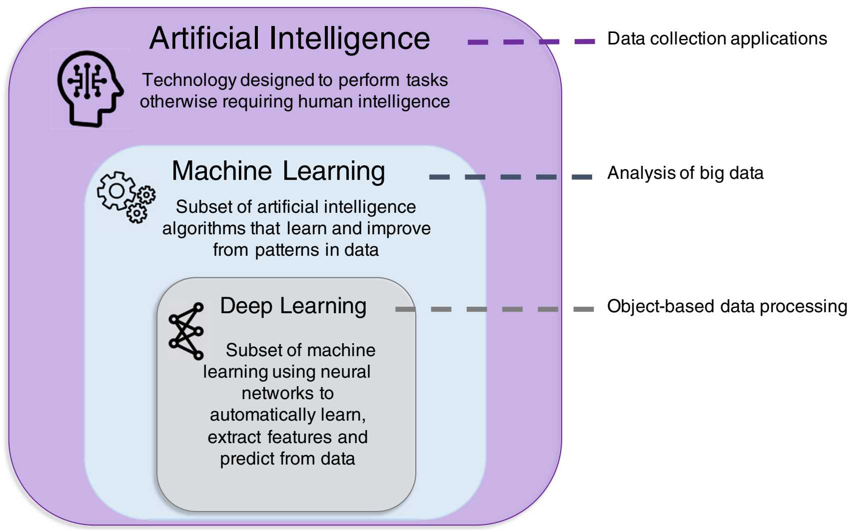

Figure 1. Example Uses of Artificial Intelligence, Machine Learning, and Deep Learning in Ecological Monitoring

collection or species identification, to complex machine learning algorithms that can learn to make better predictions by detecting patterns in data. Deep learning goes one step further than other machine learning techniques by automatically learning and extracting features from data[5] (Figure 1). Deep learning is thus becoming sort-after in monitoring to process raw images, videos, and audio, but we are yet to see its full potential. Integration of citizen science and AI has the potential to transform monitoring by expediting manual processing and analysis of big data sources,[13,14] possibly catalyzing scientific breakthroughs.[13]

Ecological monitoring typically involves *data collection* and *data processing* where AI and citizen science approaches can be complementary and valuable, and *data analysis*, where scientists can use machine learning to ask questions of processed data (Figure 2). Throughout, we discuss ecological monitoring in the context of *data collection, data processing*, and *data analysis*—and describe how citizen science, AI or the integration of both can maximize outcomes for scientists and conservation managers, in the context of *data collection, data processing*, and *data analysis*.

We first describe how citizen science and AI are currently used for data collection and processing. We then explore the opportunities, challenges, and complementarities of citizen science and AI for ecological monitoring. We identify key areas of overlap that support integration of the techniques for data collection and processing, and highlight key project attributes for managers and conservation practitioners to consider when applying citizen science, AI, or their integration for data processing.

EXISTING USES OF CITIZEN SCIENCE AND AI IN DATA COLLECTION AND PROCESSING

Citizen science and AI support the collection of big data. Citizen science monitoring projects involving accessible locations and charismatic species receive the lion's share of participation,[15–17] but projects collect data on a diverse range of topics, including pollution and climate change as well as habitats and species.[17] Keen volunteers can, for example, monitor water quality (FreshWater Watch[18]), seagrass (e.g., SeagrassSpotter[19]), mangroves (e.g., Mangrove Watch[20]), coral reefs (e.g., Coral Watch[21] and Reef Check[22]), marine fishes (e.g., Redmap[8] and Reef Life Survey[23]), bumblebees (e.g., BeeWatch[24]), and birds (e.g., eBird[25]). Involving citizen scientists in data collection can enhance the spatial and temporal scale of projects beyond what is considered practical for traditional ecological monitoring where all work is conducted by a small team of scientists.[6,10,11,17] The scale of human data collection can be further increased with sensors (e.g., cameras and acoustics) and smartphones. AI is being incorporated into devices for ecological monitoring with increasing complexity and application. For example, citizen science smartphone applications can include AI algorithms to recognize geographic locations where scientific data needs have not been met, incentivizing participants to increase monitoring effort at those locations through competition.[26] Acoustic loggers can be programmed to identify and record animal calls using classification algorithms, with such technology becoming cheaper, smaller, and more user friendly (e.g., AudioMoth).[4] Autonomous robots and unmanned aerial vehicles can be equipped with smart sensors to allow for wildlife surveillance in remote or difficult to access places,[27,28] while in the oceans automated monitoring buoys can collect data on algal blooms.[29]

Citizen science and AI supercharge the processing of big data. AI can be faster and equally or more accurate than humans in identifying subjects of interest, as demonstrated in acoustic classification of environmental sounds[4] and image classification of African megafauna,[30] coastal fishes,[31] birds,[32] and plant diseases.[33] Automated classification of visual, acoustic, and spatial data using deep learning allows us to provide larger datasets for use in models of complex ecosystems, or automatically monitor text-based platforms, such as online monitoring of the illegal wildlife trade.[34] Using newer deep learning techniques, footage of animals can be rapidly and accurately processed after algorithms are trained to recognize species from labeled images.[30,35,36] This "supervised" deep learning requires manual image labeling,[5] thus integration with citizen science can vastly accelerate processing time by harnessing large-scale citizen science communities to capture and label images used to train deep learning models.[30,36] Although AI could theoretically replace the need for manual processing by humans (see Christin and colleagues[5] and LeCun and colleagues[37]), the integration of people power and computer power can create hyper-efficient and complex social machines, provided image labeling accuracy is high[13] (see section on Accuracy below). This integrated capability is beginning to be realized through online citizen science databases, such as Wildbook,[38] Zooniverse (zooniverse.org), and iNaturalist (inaturalist.org) (see Ceccaroni and colleagues[12]).

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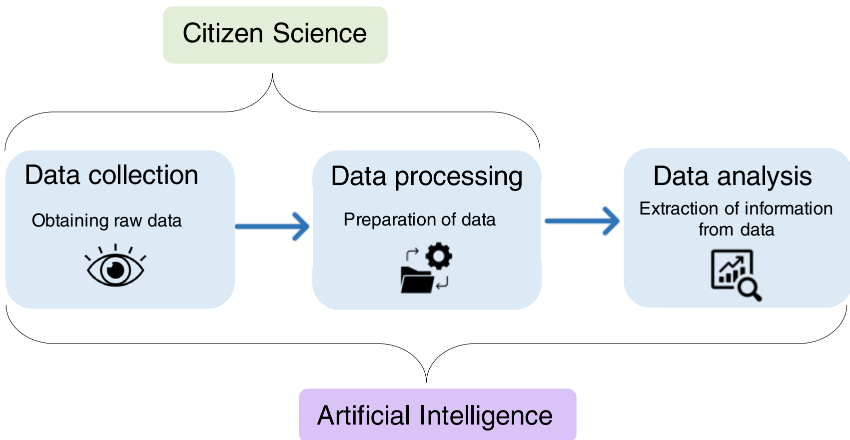

Figure 2. Typical Roles of Citizen Science and Artificial Intelligence in Data Collection, Processing, and Analysis

Note, there is a growing movement to involve citizen scientists at all stages of the scientific workflow, including data analysis.

THE OPPORTUNITIES, CHALLENGES, AND COMPLEMENTARITY OF CITIZEN SCIENCE AND AI FOR ECOLOGICAL MONITORING

Here, we summarize the opportunities and challenges of using citizen science and AI techniques for ecological monitoring under six key categories, while highlighting opportunities arising from citizen science-AI integration (Figure 3). The categories are efficiency (opportunities only), accuracy, discovery, engagement, resources, and ethics (challenges only). It is worth noting that not all projects utilizing citizen science, AI, or integration will be successful, and unsuccessful attempts are unlikely to be published. Our findings, based on the published literature, are thus likely more representative of successful, well-supported projects, and could be considered exemplars of such projects.

Efficiency

Citizen science can expand the spatial and temporal scale of projects beyond what is possible in traditional ecology. Such large-scale, long-term data collection projects are critical for tracking global change impacts on biodiversity.[8,17] Furthermore, citizen scientists can expedite the often rate-limiting step of processing data, for example, by processing camera trap or aerial images and other repetitive tasks.[13,30] There is also great potential for AI to efficiently automate laborious tasks (e.g., video analysis) through machine learning (and particularly deep learning[30]), allowing researchers to focus their expertise on ecological questions.[34] Given its speed, deep learning is useful in proactive conservation interventions, such as averting human-wildlife conflicts or detecting poachers in real time,[34] and providing rapid wildlife population estimates.[30] But better still may be the creation of complex social machines that integrate human and computer-based data processing.[13,14,35] One such example is the Human/Computer Learning Network established by eBird, which allows for the exchange of feedback and active learning between humans and machines.[25] Such integration can produce results superior to either one alone, while allowing for serendipitous discovery.[13] Thus, humans can be seen as a part of greater automation, not simply as an alternative to automation.[13,14]

Accuracy

Traditional science has sometimes considered data collected by citizen scientists as too biased to be usable.[9,17] The inclusive nature of many citizen science projects means there is often little discrimination of participants based on low literacy, training, continued enthusiasm, or sense of moral obligation.[39] Despite some mistrust of citizen science data, high accuracy is attainable with participant training[8] or quality control,[5] including through the use of AI techniques. Furthermore, many citizen science participants are enthusiasts and already knowledgeable of the subject matter, such as in the case of recreational fishers and divers (e.g., Redmap[8]) and birders (e.g., eBird[25]). eBird even ranks user's data quality based on an algorithm that detects discrepancies between users' bird lists provided by a user and other users.[25] Given appropriate safeguards, citizen scientists can label and train large datasets that are subsequently processed using deep learning algorithms. The result is AI-citizen science integration that can be as or more accurate than humans in the classification of images[36] and sounds.[43] Irrespective of who collects or labels data, there is a need for redundancies in deep learning systems to safeguard against false detections, particularly false negatives, for which consequences can be great (e.g., failure to automatically detect poachers near animals, or dangerous animals near people).[34]

Discovery

Citizen science projects have assisted scientists in a number of important discoveries in ecology.[17,39] For example, citizen scientists helped scientists uncover poleward range shifts of butterflies,[44] and marine fish[8] and invertebrates[45] in response to a changing climate. Citizen science projects may also increase the likelihood of serendipitous discovery by having more eyes on the ground to notice the unexpected,[40] through high social interactivity of participants and the ability of the human brain to notice anomalies in pictures and patterns.[13,39] An example is the chance astronomic discovery of "Green Pea" galaxies, where a number of volunteers noticed unusual green blobs while classifying images in a million-galaxy dataset.[46] While AI in isolation is not yet renowned for serendipitous discovery in ecology, unsupervised AI may hold potential in this field.[37] In unsupervised AI, the algorithm learns directly from raw data without a labeled training dataset.[5] Furthermore, there is much potential for deep learning to go beyond the classification of large datasets, to prediction and online monitoring of text.[34] Thus, the integration of citizen science and AI could lead to future discoveries and predictions that we are yet to fully appreciate.

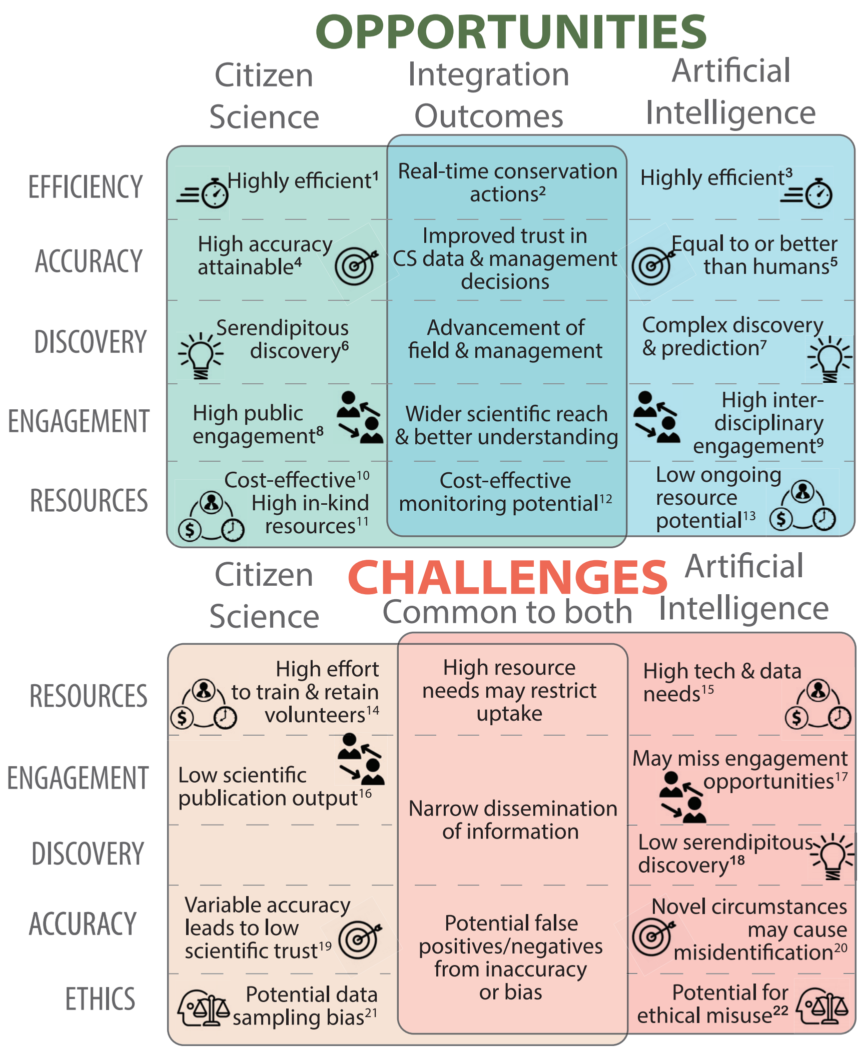

Figure 3. The Opportunities (Top) and Challenges (Bottom) of Citizen Science (Left) and Artificial Intelligence (Right) for Ecological Monitoring, Including Integration Opportunities (Top Center Overlap) and Challenges Common to Both

Categories are efficiency (opportunities only), accuracy, discovery, engagement, resources, and ethics (challenges only) across each row of text. Superscripts refer to the following supporting references: 1,[11,30] 2,[34] 3,[34,35] 4,[6,8,30] 5,[31,33] 6,[13,39,40] 7,[34] 8,[8,18,40] 9,[14,34] 10,[40] 11,[17,18,40] 12,[13] 13,[16] 14,[18,39] 15,[34] 16,[15,17] 17,[13] 18,[13] 19,[17,39] 20,[34] 21,[18,39,41,42] and 22.[34]

Engagement

Public engagement is fundamental to citizen science.[8] Through engagement, citizen science projects increase public trust in scientific enterprise, build communities of interested participants, involve the public in policies and debates, such as those regarding action on climate change and environmental sustainability, and foster education, literacy, and awareness of science in the general public (see Lukyanenko and colleagues[39]). From more-informed and empowered communities come benefits to researchers, monitoring agencies, and policymakers, through increased environmental data and support for land-use and resource decision-making.[18] Citizen science has enhanced the relationship between ecologists and the public,[11] and indeed the relationship between the public and the natural world.[47] For example, as people migrate to cities and lose touch with nature, citizen science can increase emotional and cognitive connections to nature and make participants more supportive of conservation efforts.[47] However, rigorous science needs to underpin citizen science to ensure trust in data and encourage peer reviewed publication of findings.[6,8,9,17,48] There is great potential to strengthen the public's engagement in the scientific process through citizen science, enabling large data resources to be better utilized to understand and address global change impacts.[17] AI too provides opportunities for interdisciplinary collaboration between ecologists and computer scientists,[3,5,14] but public engagement is arguably lower when using AI approaches alone.

Resources

The greatest financial savings for research involving citizen scientists come with data collection and data processing. In 2015, the in-kind contributions of data collection and processing from over one million volunteers from 388 English-speaking citizen science biodiversity projects was estimated to be between USD 667 million and 2.5 billion annually, with projects covering comparable spatial scales and running for longer than most government-funded projects.[17] The cost of collecting similar data via traditional means is often greater. For example, one study found the ~€4 million annual cost of 395 monitoring projects across Europe would have been 3-fold greater had no volunteers been involved.[49] Nevertheless, the time and financial costs of training and managing citizen scientists can be considerable, and funding acquisition for citizen science projects challenging,[50] potentially because of assumptions that using volunteers make projects cost-effective. Furthermore, the opportunity cost of failed citizen science projects is not typically reported.

The greatest financial benefits from AI come with data processing and data analysis, where automation frees up scientists' time and funding, and computing power helps explore and analyze big data. However, the cost to invest in the specialist staff and computing power required to design, train, test, use, and maintain AI algorithms can be substantial, and thus may be impractical or inaccessible for one-off applications. Improved understanding of the potential benefit of collaboration across disciplines may help overcome uncertainty of use. Increasingly, ready-made browser-based tools requiring little modeling expertise are available at a fraction of the cost. For instance, the Automated Remote Biodiversity Monitoring Network provides tools for scientists to identify species from audio recordings using automated sound identification,[51] while Wildbook allows users to train AI algorithms to automatically identify species from images collected by citizen scientists, with costs for project setup ranging from USD 10,000–20,000.[16,38] The Zooniverse Project Builder saves considerable time and money by providing a free, user-friendly platform to set up online projects for citizen scientists to classify data that can be used to train AI algorithms.[13] Alternatively, complete outsourcing of AI data processing and analysis is now possible, with costs charged per unit of data (e.g., minute of audio).[16] For data analysis, utilizing AI machine learning can power analysis when few data exist for a species, such as all species listed as Data Deficient under the International Union for Conservation of Nature (IUCN) Red List. Here, the use of models could save 68% of the USD 323 million required to collect additional data by filling in data gaps by learning from data already available.[52] Regardless of the application, the costs required to process and analyze big ecological datasets using AI continue to diminish with increased technological capacity and demand.[34]

Ethics

As with any scientific technique, there is a need for citizen science and AI to collect and process data and apply analytical tools responsibly. For example, it can be difficult to avoid sampling bias in citizen science projects, as participants may collect or process data based on personal preferences for desirable locations, weather, seasons, or study subjects.[18,40,42] These biases can be discouraged as part of participant engagement, and should be accounted for during analysis to produce results that are meaningful, and not misleading.[41,42] Citizen science projects often make data publicly available,[17] bringing potential risks to data sharing if protocols are not put in place, such as incidental increases in poaching or habitat disturbance by visitors. But not sharing such data can also unnecessarily impede conservation actions.[40,53] Poachers using online information to exploit vulnerable species is a possible drawback of sharing data collected using either technique, but AI could also be used to detect poachers in real time, both in the field[34] and online through text recognition.[54] Indeed, using AI tools for data processing and analysis can lead to a greater and faster understanding of ecosystems if used correctly, with appropriate protocols, and in an ethical framework.[55] Public data sharing and presentation fosters project ownership and social capital with flow-on benefits to data collection and conservation outcomes, while AI facilitates rapid analysis and presentation of data. While user-friendly AI software is becoming more readily available, part of the difficultly in non-experts using these tools is that the mechanics behind the software can be hidden, creating a black box that makes trouble-shooting difficult.[34] Furthermore, if and when citizen science data are integrated with AI techniques, it is important that citizens understand how their contributions are used,[12] such as the transparency adopted by eBird in making information on their integrated Human/Computer Learning Network species identification system available.[25,56]

ATTRIBUTES TO CONSIDER FOR CITIZEN SCIENCE, AI, AND INTEGRATED PROJECTS

We define and describe eight key project attributes that may differ in relative importance when considering the implementation of citizen science or AI for ecological data processing (Figure 4). The balance between one or both methods offers a preliminary guide to project managers but need not be a deterrent. We suggest that most conceivable issues are surmountable. Managers of integrated projects should assess where their project sits in relation to these considerations.

Financial Resources

One of the biggest considerations for any ecological monitoring project is financial resources (Figure 4). While participants in citizen science contribute to financial overheads by volunteering their time and other personal resources, the cost to engage, train, and potentially equip numerous participants can be significant. For projects seeking to implement AI, the need for potentially costly hardware, software, and paid expertise for utilizing AI (see section on Resources above) are a consideration. However, as computing power and AI techniques become more financially accessible, AI uptake and the integration of citizen science and AI in ecological monitoring will likely become available for even modestly funded projects.

Public Engagement

Public engagement is a critical aspect of projects involving citizen scientists (Figure 4; see section on Engagement above). Citizen science projects have great capacity to authentically engage the public with science, the project, and the natural environment.[47,57] This statement is less true, in general, for AI-only projects. However, through integration, AI technology can help ecological findings be more rapidly accessible to the public, increasing levels of understanding, interest, and engagement in the scientific process.

Subject Charisma

Charismatic species can be important for encouraging citizen participation and enthusiasm,[16] much like how charismatic species or "flagships" often attract the most conservation funding.[58] However, there are successful citizen science projects that focus on typically non-charismatic subjects, such as those on plants, worms, and ice (see Conrad and Hilchey[50]), and even the least charismatic species can attract conservation funding with targeted marketing campaigns.[59] Unique solutions to projects on such species can also overcome any perceived lack of interest by utilizing games to both attract and sustain citizen science engagement.[60] Therefore, we suggest that, although subject charisma is more important for citizen science relative to AI (Figure 4), it need not prevent implementation of successful citizen science, or integrated projects. Projects focused on less charismatic species may benefit from integration as automated data processing means fewer volunteers are needed.

Subject Identification

Subject identification relates to the difficulty for humans to identify subjects in terms of taxonomy (e.g., identifying species of birds) or enumerating very small animals (e.g., counting plankton). Both may need specialist training to develop an in-depth knowledge of the subjects and other technical skills to achieve the task. Citizen science projects benefit from easily

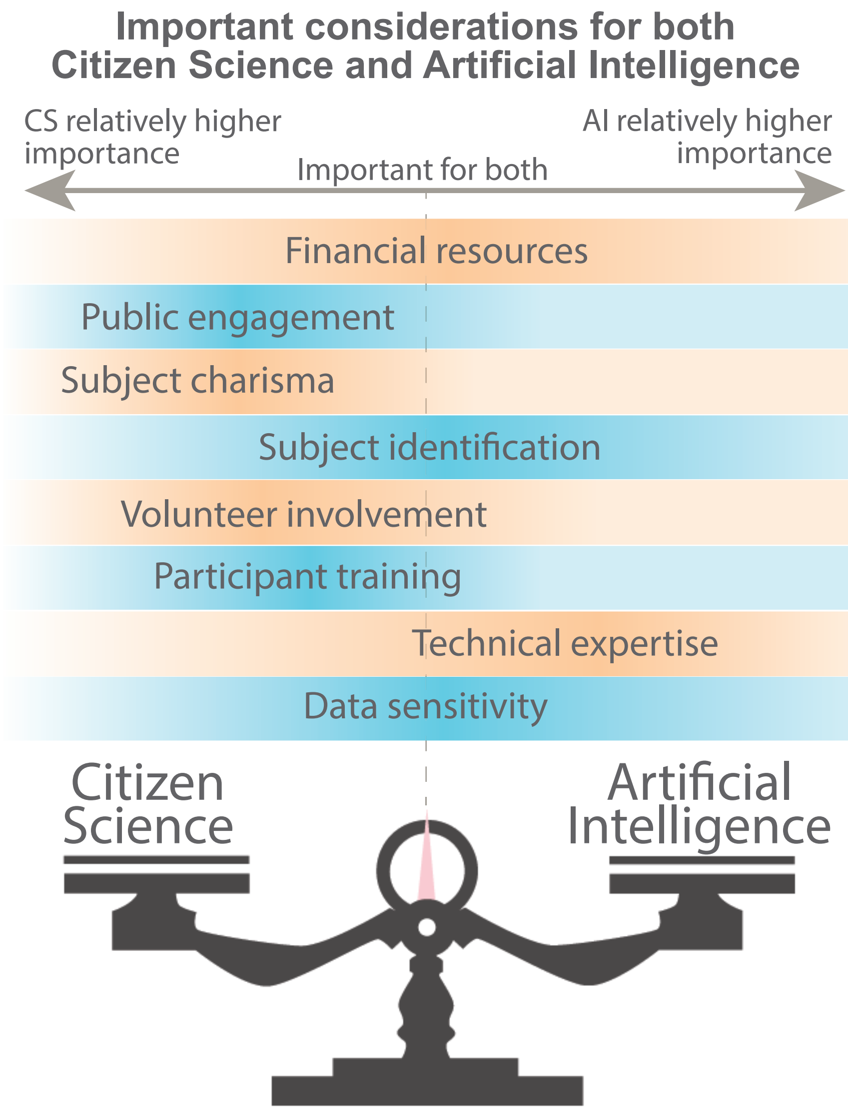

Figure 4. Important Project Considerations when Implementing Citizen Science or Artificial Intelligence for Ecological Monitoring

Project attributes placed toward either citizen science (CS) or artificial intelligence (AI) indicate relatively higher importance for that technique, but not a lack of importance for the other technique. Project attributes placed in the middle indicate equally high importance for both CS and AI. All project attributes would be important to consider for integrated approaches. Placement of attributes is guided by the literature and may change over time.

identifiable and distinguishable species (when participants are not already enthusiasts of the topic, for example, see Kelling and colleagues[25]). AI accuracy outputs rely on accuracy of labeled data inputs[34] (unless using unsupervised methods), thus making species identification an important consideration, even for expert researchers, assistants, and students who train models (Figure 4). The integration of citizen science and AI thus also benefits from ease of subject identification because, typically, citizens are collecting data and potentially training AI models (e.g., annotating images). In studies involving the identification of multiple species, a combination of citizen and expert identification may be necessary. For example, it may be possible to rely on citizen science to identify individuals that are easily distinguishable, while those that are more difficult may need to be referred (possibly automatically) to experts for clarification (see Kelling and colleagues[25]). This approach may be of great benefit in reducing the expert time required in large-scale projects assessing whole ecosystems or taxonomic groups (e.g., nudibranchs, birds).

Volunteer Involvement

Volunteer involvement is pertinent to citizen science projects (Figure 4; see section on Engagement), and thus to the success of integrated projects that process large data sources. Opportunities to engage volunteers in AI for ecological monitoring could carry benefits for both fields. However, it is expected that fewer volunteers would be needed for integrated projects than for citizen science projects of the same scale, because AI capabilities can take over once a citizen science-led training dataset is established. Thus, to maintain the benefits of volunteer engagement, care should be taken to keep volunteers informed and involved.[13,25]

Participant Training

Projects that utilize citizen scientists typically need to train the participants, adding to the cost and time commitment of managers. However, when participants are enthusiasts of the subject area, less ongoing training is needed on behalf of the scientist (see section on Accuracy above). In AI-only projects, data collection, processing, and analyses are primarily conducted by experts. Where students and assistants are involved in AI, participant training is important to ensure quality. In some citizen science platforms, a level of automated feedback is beginning to emerge to assist training participants.[24,25] For example, the use of a natural language generator in the bumblebee identification tool BeeWatch gives feedback to participants when they misclassify bumblebees based on morphology, in a bid to improve training through engagement, in turn improving results and participant retention.[24]

Technical Expertise

In general, utilizing AI for data processing requires a higher level of user expertise than utilizing citizen scientists (Figure 4). However, outsourcing AI for data processing is now possible, circumventing the need for in-house user expertise (see Kwok[16]), while accessibility and usability of algorithms is rapidly improving.[5] When integrating citizen science and AI, the level of user expertise is dependent on a range of variables and can be controlled by decisions about how to utilize either technique in the early stages of project development (e.g., who will develop and use AI).

Data Sensitivity

Data can be sensitive; for instance, if it reports on the locations of rare or highly valuable species (see section on Ethics above). It is important to consider the ramifications of both collecting and processing sensitive data regardless of whether using citizen science or AI, or both (Figure 4). However, the issue of data sensitivity can largely be controlled for with a suite of protocols and guidelines available that can ensure the sensitivity of data does not inhibit successful integration of citizen science and AI.[53]

CONCLUSIONS

The complementarity of AI with citizen science means that ''the whole is greater than the sum of its parts.'' The strategic integration of citizen science and AI can produce synergistic outcomes to enhance ecological monitoring by providing rapid, accurate, and comparably cheap data collection and processing, thus supercharging conservation outcomes and management decisions.[36,42,56] However, there are complexities to combining citizen science and AI approaches. A range of attributes should be considered by project managers, and we argue these considerations are largely surmountable for most integrated citizen science-AI projects. Furthermore, coupling the public engagement strategies of citizen science with advanced scientific techniques of AI increases the likelihood of multi-stakeholder and multi-sector accord on issues of public and scientific interest. There is a real need for greater recognition of the benefits of citizen science, AI, and particularly their integration, for improving methods in ecological monitoring, enhancing understanding of the natural world by scientists and citizens, and promoting positive outcomes for environmental management.

ACKNOWLEDGMENTS

We acknowledge funding support from: C.J.B. and R.M.C.—Discovery Project (DP180103124) from the Australian Research Council; E.C.M., M.S., C.J.B., C.A.B., E.M.D., R.M.P., V.J.D.T., and R.M.C.—The Global Wetlands Project, supported by a charitable organization which neither seeks nor permits publicity for its efforts.

AUTHOR CONTRIBUTIONS

Conceptualization, E.C.M., C.J.B., V.J.D.T., and R.M.C.; Investigation, E.C.M., M.S., E.M.D., and R.M.C.; Writing – Original Draft, E.C.M., M.S. and E.M.D.; Writing – Review & Editing, M.S., C.J.B., C.A.B., E.M.D., M.A.H., R.M.P., V.J.D.T., R.K.F.U., and R.M.C.; Visualization, E.C.M., C.A.B., E.M.D., R.M.P., M.A.H., and R.K.F.U.; Supervision, R.M.C.; Funding Acquisition, C.J.B. and R.M.C.

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Dr. Eva McClure is a Research Fellow at Griffith University with an interest in combining her experience in marine field ecology with her enthusiasm for connecting people with nature, while exploring the application of cutting-edge technology to solve real-world data challenges.

Professor **Rod Connolly** leads a multidisciplinary team through the Global Wetlands Project, Griffith University, that uses science to support solutions for critical issues in coastal conservation through AI and online tools that create positive change. Griffith authors include **Dr. Christopher Brown**, Research Leader and marine ecosystem modeller, who works on bringing ecological complexity to the planning tools used to inform environmental decisions; **Dr. Michael Sievers**, experimental and field ecologist interested in ecosystem assessment frameworks; **Dr. Christina Buelow**, quantitative ecologist interested in establishing confidence in coastal ecosystem conservation; **Dr. Ryan Pearson**, community and population ecologist with leadership experience in citizen science and automation projects; **Ellen Ditria**, PhD candidate investigating AI applications for automated systems to improve marine conservation; and **Dr. Matthew Hayes**, interested in the effects of a changing climate on habitat and species range expansions.

Dr. Vivitskaia Tulloch is a Banting Postdoctoral Fellow at the Conservation Decisions Lab, University of British Columbia, Canada. Viv is interested in how natural and human disturbances affect biodiversity and natural resources. Viv has expertise in both applied and theoretical conservation biology including marine and terrestrial reserve design, using decision theory and economics to solve conservation problems, and ecosystem modelling and cumulative impact assessments for interacting species. She is currently developing ecosystem-based models to prevent decline of threatened and endangered resident killer whales and salmon across the Pacific west coast of Canada.

Dr. Richard Unsworth is a senior lecturer in marine biology at Swansea University and a founding director of the marine conservation charity Project Seagrass, where he leads the global citizen science project SeagrassSpotter.org. His scientific expertise lies in the ecological structuring processes of marine systems and the implications of these systems for society.