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Artificial intelligence and automated monitoring for assisting conservation of marine ecosystems: A perspective

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Conservation of marine ecosystems has been highlighted as a priority to ensure a sustainable future. Effective management requires data collection over large spatio-temporal scales, readily accessible and integrated information from monitoring, and tools to support decision-making. However, there are many roadblocks to achieving adequate and timely information on both the effectiveness, and long-term success of conservation efforts, including limited funding, inadequate sampling, and data processing bottlenecks. These factors can result in ineffective, or even detrimental, management decisions in already impacted ecosystems. An automated approach facilitated by artificial intelligence (AI) provides conservation managers with a toolkit that can help alleviate a number of these issues by reducing the monitoring bottlenecks and long-term costs of monitoring. Automating the collection, transfer, and processing of data provides managers access to greater information, thereby facilitating timely and effective management. Incorporating automation and big data availability into a decision support system with a user-friendly interface also enables effective adaptive management. We summarise the current state of artificial intelligence and automation techniques used in marine science and use examples in other disciplines to identify existing and potentially transferable methods that can enable automated monitoring and improve predictive modelling capabilities to support decision making. We also discuss emerging technologies that are likely to be useful as research in computer science and associated technologies continues to develop and become more accessible. Our perspective highlights the potential of AI and big data analytics for supporting decision-making, but also points to important knowledge gaps in multiple areas of the automation processes. These current challenges should be prioritised in conservation research to move toward implementing AI and automation in conservation management for a more informed understanding of impacted ecosystems to result in successful outcomes for conservation managers. We conclude that the current research and emphasis on automated and AI assisted tools in several scientific disciplines may mean the future of monitoring and management in marine science is facilitated and improved by the implementation of automation.

KEYWORDS

artificial intelligence, automation, ecological monitoring, marine conservation, conservation management, machine learning, restoration

Introduction

Successful conservation of marine ecosystem function and biodiversity is critical for sustaining the services they provide (Ward et al., 2022). Understanding complex ecosystem processes that are imperative for decision-making and effective conservation management requires ecological insight over varying temporal and spatial scales (Lindenmayer and Likens, 2009). These insights include quantifying ecological responses to environmental change and providing ecological data to develop informed ecological syntheses and prognostic ecological models. Such syntheses and models act as platforms for collaborative studies, promoting multidisciplinary research and providing information to support evidence-based policy, decision making, and management of ecosystems, by implementing both passive and active conservation to achieve optimal conservation outcomes (Lindenmayer et al., 2012; Possingham et al., 2015).

Both passive and active conservation approaches are important and complementary strategies to ensure the recovery of impacted ecosystems. Passive conservation approaches aim to lessen or remove the impact of environmental stressors to promote the natural recovery of habitats, and often address issues that may inform policy in areas such as poor water quality or pollution (Perrow and Davy, 2002; Morrison and Lindell, 2011). Ongoing monitoring to determine the success of passive conservation approaches does not often require understanding complex ecological processes and is often the cheaper alternative. Reduction or cessation of a stressor is often the primary goal, such as removal of agricultural grazing or reduction in pollutants, and does not often test the systems' response to the management action, but the level of certainty in achieving the goal is high, for example, agricultural grazing was either reduced or it was not (Perrow and Davy, 2002; Morrison and Lindell, 2011; Williams, 2011) Active conservation, such as restoration efforts, is often attempted at relatively smaller scales than passive restoration, however, this is where current efforts in management are often comparatively less economical and successful (Díaz-García et al., 2020). Currently, the costs for active conservation efforts are high. For example, the global median cost to restore 1 hectare of marine habitat is 80,000 USD, however, due to a number of uncertainties within the restoration process, the real costs are more likely to be 2-4 times higher (Bayraktarov et al., 2016). Conservation management through ecosystem restoration of degraded habitats is of particular interest, with the United Nations hailing 2020-2030 as the Decade on Ecosystem Restoration. While the implementation of ML algorithms in statistical analysis in marine ecology is widespread, automated solutions for monitoring and management are rarely attempted (Perring et al., 2018), particularly for more localised or smaller-scale conservation projects. Many marine active conservation efforts are expensive and achieve average results or fail (Saunders et al., 2020). This may be due to insufficient resources to effectively monitor the ecosystem response long-term or to manage and adapt effectively after implementation. However, managers often face challenges in obtaining data for active conservation over appropriate spatio-temporal scales and high resolutions due to several difficulties such as the long-term financial support required, and creating and maintaining an appropriate monitoring design to accurately detect changes in the environment.

Despite the need for long-term monitoring projects to determine the success of active conservation efforts, they remain uncommon, as ongoing funding, support, or partnerships are challenging to sustain. Funding agencies and investors are more likely to invest in new and innovative projects, which pressures researchers to pitch their projects as *novel*, rather than *necessary* monitoring (Keeling, 1998; Nisbet, 2007). Funding for active conservation projects is often scarce, and budgets may be revised due to external economic factors, such as the global economic changes resulting from COVID-19 (Pearson et al., 2020). In a time of financial uncertainty and projected economic recessions for many countries, long-term ecological studies may be considered non-essential spending in the short term. Funding may also be split over shorter projects to match the length of active government administration and funding cycles (Lindenmayer et al., 2012). For example, funding from the National Science Foundation (USA) for long-term ecological projects has decreased significantly in recent years, while funding for short-term projects (4 years or fewer) has increased (Hughes et al., 2017). Additionally, small sample sizes and inefficient monitoring at inappropriate spatio-temporal scales can impede the detection of ecologically relevant changes. Consequently, inadequate monitoring may result in poor management decisions that are detrimental to an ecosystem, for example introducing ecological traps that negatively affect species' fitness, despite being under the guise of an environmentally conscious contribution to the public or funders (Legg and Nagy, 2006; Hale and Swearer, 2016). Ultimately, enough data must be collected at appropriate spatial and temporal scales using robust, long-term, and reproducible monitoring approaches. Additionally, the ability of monitoring practices to assess the accuracy or precision of collected data is often not evaluated (Jones et al., 2015), and there can be a disparity between monitoring and management scales. Often there is a need for managers to discuss Thus, there is a need for accurate, scalable, cost-effective, and accessible solutions to assist in informing management at the appropriate scales at which management occurs (Dietze et al., 2018).

Automated monitoring facilitated by artificial intelligence (AI) can provide a cost-effective solution to provide tools for monitoring impacted and restored ecosystems over more relevant spatial and temporal scales. Automation is defined here as the use of technology to replace or reduce human intervention. Automation has been adopted in many industries, from automotive to finance, by replacing manual efforts with computer programs or robotics (Lee, 1998; Gorlach and Wessel, 2008). Machine learning (ML), a subset of AI, has been fundamental to automation. ML algorithms use experience through exposure to data to improve model performance and, as a result, can make accurate predictions from large volumes of data obtained in an automated framework (Mohri et al., 2018). After implementation, automated systems should require minimal input to report on the state of an ecosystem and are potentially more cost-effective. Novel monitoring approaches using automation and AI have consequently shown a marked decrease in running costs after implementing automated systems (e.g. Chen et al., 2015). González-Rivero et al. (2020) reported, for example, that the automated processing of image-based data from coral reefs using ML technologies resulted in a 99% cost reduction over traditional methods, at 200 times the speed. Therefore, the implementation of automated monitoring is likely to have high short-term costs but low ongoing costs, amenable to most funding cycles, and potential to overcome the funding barrier for long-term monitoring as well as expand data collection across greater spatial and temporal scales. These cost reductions demonstrate that harnessing the power of AI for automated long-term monitoring can be one of the solutions to conservation management funding constraints. In addition to cost and time reduction, incorporating automation and AI into management pipelines can expand our ability to manage impacts on ecosystems effectively by providing data at the appropriate resolution to address management needs and inform policy. The additional data collected across greater temporal and spatial scales, and processed *via* automated monitoring methods, provides more information on the state of an ecosystem, which in turn allows for a better understanding of the environmental processes operating within the system (Figure 1). This increased access to data, and subsequent flow-on effects, follow the theory of the data-information-knowledge-wisdom pyramid that can lead to more effective management decisions by incorporating more, and useful inputs into the decision-making process for managers to consider (Intezari et al., 2016).

Here, we provide a perspective on the potential of AI technology to transform conservation monitoring and management through automation. We first summarise the challenges and needs in ecological monitoring around the collection, transfer, and processing of big data, with a focus on overcoming the unique challenges of marine environments and the benefits that provide, which lend themselves more to the needs of active conservation management, as these approaches usually require more iterative approaches to evaluate management impact. We note some of the current implementations of AI and automation technologies and complementary techniques, not only in ecological sciences but also in other disciplines that may have implications for our capacity to effectively monitor marine ecosystems and inform management, addressing the areas of research that require further investigation in proving the scalability and feasibility of these tools. Additionally, it is important to note that these tools still need to be relevant and useful, and the appropriate approach should be discussed by managers and stakeholders when setting objectives and considering the monitoring design within their management framework (McDonald-Madden et al., 2010).

Secondly, we identify current and emerging methods that provide evidence for the potential of end-to-end, fully automated methods to assist decision-making to suit the needs of both passive and active conservation managers for marine and coastal habitats by way of appropriate big data analysis, decision support, and management action, that more fully utilise the benefits an automated monitoring approach provides. The implementation of these automated practices provides managers with the capacity to rapidly assess management impact to determine changes and iteratively adjust management actions accordingly (supporting adaptive management approaches), at all stages of the management process from objective setting to implementation and monitoring. Following the conceptual logic of the Driver-Pressure-State-Impact-Response (DPSIR) framework as an

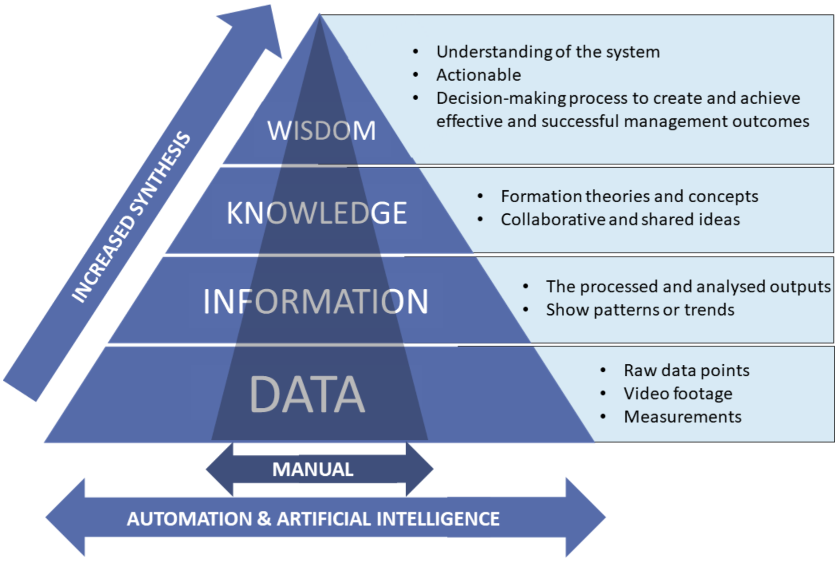

FIGURE 1
Implementing AI facilitated, automated methods to collect and process data allows users to increase the scope, resolution, and breadth of conservation studies by providing managers with more information, and there a greater capacity to share and form knowledge on the target ecosystem. Coupled with novel machine learning techniques to analyse and predict outcomes, this may provide a greater understanding of the system, leading to a greater capacity to effectively manage degraded ecosystems. The removal of the processing bottleneck adds to the increased speed at which the data is transferred and translated into useful information and utilised to create management decisions in a timely manner.

example, as management actions are adopted the automated pipeline provides information on the speed and strength of the environmental response, and the management cycle continues (Figure 2). Importantly, many of the approaches and technologies presented in this perspective are at different stages of research and development, therefore may be implemented faster in a "semi-automated" approach, where parts of the management cycle still rely on manual intervention, such as data transfer from device to computer. Such approaches may allow the adoption of these automation techniques at a more comfortable pace for users or allow users to target areas where the need for automation is greatest. This may allow for more realistic implementation of automation tools for projects where prohibitive costs do not outweigh the benefits. We demonstrate how automation can support managers in obtaining useful information for monitoring the outcomes of a conservation decision, and adapting where necessary'

Automated monitoring

Non-invasive data collection

The reliance on manual efforts for monitoring means that a high proportion of monitoring project budgets are spent on data collection, limiting the breadth and scope of a project (Caughlan and Oakley, 2001; Weinstein, 2018). In addition to the high cost and effort which limits sample sizes, the requirement for manual data collection may also bias sampling towards sites that are easily accessible to humans, which is particularly relevant due to the limited accessibility of many marine or coastal environments. These issues have meant that manual data collection in ecological sciences is rapidly being supplemented or replaced by remote sensing and automated methods to obtain coveted "big data" (Kimball et al., 2021). Big data is becoming an important facet of ecology and has challenged the epistemology of scientific disciplines, as it disrupts and reconfigures how research is conducted (Kitchin, 2014; Durden et al., 2017). Big data broadly refers to massive volumes of data that are not feasibly able to be handled using manual methods. More specifically, to be defined as big data it must possess the qualities of the "five V's"; variety, volume, velocity, veracity, and value (Anuradha, 2015; Cappa et al., 2021). These qualities define big data as different types and large volumes of data created and transferred at increasing speeds that are generally reliable, and of value, to a user. Using big data enables a better understanding of systems and processes as users have access to far greater sample sizes to accurately reflect a greater variety of real-world scenarios and increase statistical power in data analysis. The increased development, prevalence, and accessibility of new technologies have enabled researchers to access big data at higher spatial and temporal resolution using remote sensing.

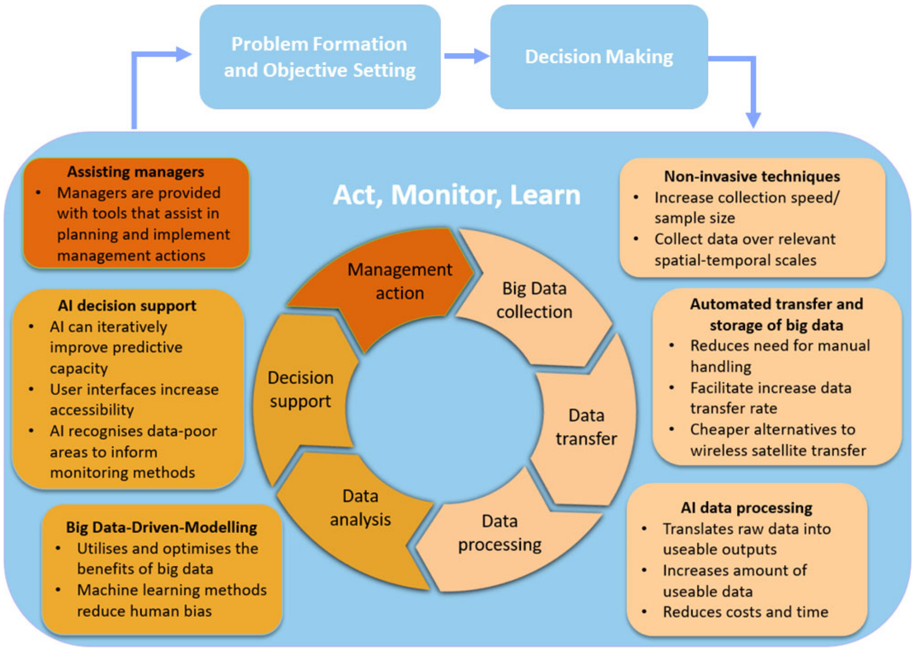

FIGURE 2
Conceptual, cyclical diagram for the capacity for an automated system to support managers at all stages, from baseline data collection to objective setting, to ongoing long-term monitoring and management actions. We summarise the main points in each step where managers may benefit from implementing an automated system to assist in achieving management outcomes. Automation and AI technology can assist managers in learning about the environment to support problem formation and inform objective setting, as well as assist in ongoing, high-resolution monitoring to inform on the results of management actions.

Remote sensing is the science of collecting data *via* noncontact recording, often providing geospatial or environmental information (Wang et al., 2010). When implemented into wireless sensor networks, remote sensing is ideal for integrating into an automated end-to-end system. Remote sensing techniques have become increasingly sophisticated over the last decade, leading to a marked increase in obtaining big data quicker than manual methods and at a lower cost (Malde et al., 2020). However, the scale at which RS networks often collect data may not always be useful for some active conservation projects. Monitoring animal biodiversity and fitness after the implementation of management actions is important when considering the functional recovery of an ecosystem, but is rarely attempted or considered in marine ecosystem conservation (Hale et al., 2019). Additionally, the collection of ecological data on the behaviour, abundance, and distribution of animals and plants, in marine environments, presents unique challenges due to limited accessibility and visibility that are often of less concern in terrestrial environments.

A solution to the scale and visibility constraints traditional RS provides is the use of portable devices that collect image-based data. Unmanned aerial vehicles (UAVs), commonly known as drones, can provide spatial information and a much more targeted and relevant scale to managers for active conservation projects (Belmonte et al., 2020). However, while areas can be surveyed using satellite or aerial drone imagery quickly and efficiently, this method for marine environments requires good water clarity and relies on the monitoring target utilising shallow waters (Hensel et al., 2018), which may not provide information on sub-surface behaviours or distribution. Airbourne or towed LiDAR systems can provide subsurface geospatial information at high resolutions (centimetres), as well as ecologically relevant data on animal behaviour. This approach does not rely on high water visibility and has been used to collect a range of data from mapping and monitoring coral reef health to providing data to estimate seabird flight height near offshore windfarms (Collin et al., 2018; Cook et al., 2018). The uptake of collecting underwater video footage has also been rapid in the last decade as they have become a cheap and effective way to collect large amounts of data in a non-invasive manner (Lopez-Marcano et al., 2021).

New, alternative, and novel technologies to provide ecological data have begun to emerge as a potential solution to obtain information on species with even less contact. For example, eDNA (DNA collected from environmental samples such as water and soil) can be used to observe genetic data showing the presence of species in an area without the need for extensive visual monitoring (Barnes and Turner, 2016). The use of eDNA can not only detect the presence of target species, for example, the problematic Crown of Thorns Sea Star on the Great Barrier Reef, but potentially the severity (abundance) and the locations of these outbreaks (Uthicke et al., 2018; Kwong et al., 2021). Furthermore, it has been shown that it can accurately estimate the abundances of fish within enclosed water bodies, and it is even emerging as a tool to estimate fish biomass in unconstrained marine environments (Rourke et al., 2022). Unfortunately, this technology is still prohibitively expensive for many projects and requires further research to quantify its usefulness, underscoring the need for cost-effective ways to collect useful data.

Although the potential impact and importance of big data collection have been widely acknowledged in environmental monitoring, and the utilisation of technology has become more common, there are barriers to implementing automated data-collection networks in marine ecosystems. Some of these barriers are not ecosystem specific, such as lack of technical expertise, funding, transferability, accessibility, and even awareness of the existence of potentially useful technologies (Madin et al., 2019). However, the added difficulties of accessibility and associated higher costs of effectively monitoring across appropriate spatial and temporal scales are exacerbated when managing marine environments. Additionally, new and novel technologies are becoming available to collect data remotely, however, these technologies often come with a higher cost associated, at times limiting the number of units that can be purchased, and in turn, limiting the sample size collected in monitoring projects which in turn creates uncertainty in the data collected. Furthermore, manual data collection is hailed as an important tool for community engagement and education through citizen science (Pecl et al., 2019; Schuttler et al., 2019). Therefore, removing this public data collection may have negative consequences. However, it is possible to integrate AI with citizen science (McClure et al., 2020), securing the benefits of both.

Data transfer and storage

Automated collection presents a key step in big data acquisition, but the ability to transfer high volumes of raw data to centralised systems for analysis requires innovative technological solutions. Although remote sensors are widely used in environmental studies, devices often require manual extraction to download data. Automated data transfer enables researchers to continuously receive data from regions that may be logistically difficult or dangerous for humans to retrieve devices (Caughlan and Oakley, 2001). Automated data transfer suitable for long-term monitoring relies on the ability to send data to a centralised location for analysis, requiring an efficient means of wireless transfer. Currently, wireless technologies often utilise satellite or mobile phone networks to transfer environmental data (Pettorelli et al., 2018). While sometimes successful, they can be expensive and are limited in their deployment locations as they rely on proximity to these signals.

The internet of things (IoT) describes a connected network of physical devices ("things") that can collect and exchange data over the internet, extending the reach where the wireless devices can be deployed. The IoT phenomenon has exploded onto the scene in the 21st century, connecting devices and providing researchers with an efficient means of transferring data in real-time. Coupled with edge computing technology (a means of on-board data processing for remote devices), these technologies provide an elegant solution to process large image-based data files into compressed, processed data for transmission at lower costs. For example, the coupling of remote sensing and edge computing to process images and videos has been implemented within unmanned aerial vehicles to manage disease outbreaks (Li et al., 2021) and in remote underwater videos to detect and record large mobile animals (Coro and Walsh, 2021). There are still challenges in data transfer and storage that limit the scalability of these technologies such as the relatively short range of transfer, high noise, and limited bandwidth capacity of underwater wireless sensor networks which are unique challenges in marine environments (Coutinho et al., 2018). Similarly, with cabled networks, devices are limited in their deployment location as they required cabled networks to a central location, often limiting their deployment to near coastal areas. Additionally implementing these observatories requires considerable infrastructure that is often extremely expensive, and also requires scalable and accessible facilities for big data storage and transfer to users (Barnes et al., 2012). However, automatically processing videos and images to obtain ecologically relevant data to detect trends is still emerging. Further research into the feasibility and scalability of onboard data processing using edge computing to effectively monitor marine ecosystems is still needed.

Globally accessible data storage and sharing by use of cloud-based platforms can facilitate collaborative efforts and increase accessibility to existing information. This enables fast transfer of data between managers and further supports managers by integrating additional information into their decision-making processes. An example of current efforts toward data integration, democratisation, and accessibility is a newly developed platform by the Australian Institute of Marine Science and partners; ReefCloud (https://reefcloud.ai/). ReefCloud brings together cloud computing, machine learning, and advanced statistical modelling to support the integration, synthesis, and accessibility of coral reef monitoring data for managers and decision-makers. Such integrated platforms have the potential to revolutionise conservation and management efforts by creating a centralise platform.

Data processing

Raw data must be processed or transformed into usable information for analysis. This is particularly important for raw data that cannot be used without transformation into a format that computers can read, such as acoustic recordings, video and camera footage, and sonar (hereafter all described as image-based data). Deep learning techniques have been implemented to count 1.8 billion individual trees over an area of 1.3 million square kilometres from satellite images, allowing researchers to map the variability of crown diameter, coverage, and density with respect to land use and rainfall (Brandt et al., 2020). Incorporating deep learning technology into this process meant it was completed within a few weeks; a task that would have taken years to achieve with traditional methods (Brandt et al., 2020). While spatial data is relatively easy to collect *via* remote sensing, ecological data on the long-term impact of habitat conservation efforts on marine animals has historically not been well documented. Here, we focus on image-based data as it is becoming an increasingly popular method of non-invasive data collection on the abundance, behaviour, and distribution of marine species, due to its accessibility and cost-effective ability to collect large volumes of data.

Deep learning may be a solution to the manual processing bottleneck faced by managers who rely on image-based data to inform management decisions. One use of deep learning algorithms is rapidly processing large volumes of raw image-based data without the need for manual feature extraction unlike other traditional ML algorithms, and with greater accuracy (LeCun et al., 2015; Alom et al., 2019). For instance, Torney et al. (2019) used deep learning algorithms to survey wildebeest abundance in Tanzania at a rate of approximately 500 images per hour. At this rate, future survey data are estimated to be processed in under 24 hours, whereas manual processing by a wildlife expert would take up to 24 weeks. Additionally, accuracy was not compromised, with the abundance estimate from deep learning within 1% of that from the expert manual analysis. The classification of multiple coral fish species with high accuracy showed that this method was feasible in unconstrained marine environments, despite facing unique environmental challenges (Salman et al., 2016; Shafait et al., 2016). Ditria et al. (2020a) also demonstrated that deep learning algorithms are faster, more accurate, and more consistent than manual efforts in fish monitoring. While these studies show promising results, further research into other camera methods, such as automatically detecting and sizing species using stereo-cameras, remains a gap in marine research. However, if successful, may further expand our ability to collect more ecologically relevant big data to assist conservation management by providing *in situ* biomass and size data of animals in impacted habitats.

The power of deep learning as a tool for processing image-based data has been demonstrated in the last few years, however, as these techniques are relatively new within the ecological sciences, there are still substantial challenges that need further exploration. For example, understanding the level of error and confidence in the predictive model outputs are poorly understood, and the quality to which the data is processed may be different from the small-scale tests if biases are accidentally introduced, for example, if the habitat the model is trained on is different to the data it is processing (Ditria et al., 2020b). Although these errors and subsequent uncertainties may have implications in providing misleading information, the impact on population monitoring and management is still yet to be investigated in the literature. Accounting for the bias that this uncertainty introduces to ecological inference is an active area of research (Diana et al., 2020).

Currently, there are a number of gaps for potential research using deep learning as an effective and reliable tool for image processing. Most deep learning models in the ecological literature are supervised models which require large labelled datasets for training (Christin et al., 2019). However, the sparsity of labelled ecological datasets for training deep learning models presents a challenge for developing robust models. While publicly available labelled datasets are beginning to emerge as deep learning becomes more prevalent in ecology (Saleh et al., 2020; Ditria et al., 2021), there remains a need for research on the transferability of these datasets in training models for specific purposes and projects, an area known as domain adaptation (Wang and Deng, 2018). For example, a large, labelled dataset depicting a fish species from one habitat may not create a useful model to predict the same species in another habitat. However, by supplementing an existing, large training dataset of the species of interest in other habitats with a small amount of data from the target habitat, model predictions may improve without the need to obtain large amounts of specific training data (Ditria et al., 2020b). Despite the implementation of deep learning for image processing of ecologically relevant data in marine science being in its infancy, the implications for automated image-based data processing using deep learning are enormous when considering how much data can be collected, and has historically been collected, using cheap and accessible camera and video devices. However, further research into deep learning as a scalable tool to process ecologically relevant data in challenging marine ecosystems, and the integration of deep learning model outputs and ecosystem models should be encouraged to obtain accurate information on the success of conservation efforts for ecosystem function and animal health.

AI technology for evaluation and decision support systems

Data summary and analysis

The implementation of an automated monitoring process, theoretically, provides managers with robust data at an appropriate resolution to effectively detect changes in an ecosystem over larger spatial and temporal scales. This may allow managers to obtain insights that were never available previously with the aforementioned limitations of manual monitoring methods. It is therefore important that we recognise the potential information that can be obtained from these methods, and how we can obtain it using AI methods.

One approach to maximise the benefits of automatically collected big data (as defined above) is data-driven modelling (DDM). DDM utilises big data and ML algorithms (including previously mentioned deep neural networks) to find non-linear relationships and patterns between variables (Willcock et al., 2018). This modelling approach has significantly expanded empirical modelling capabilities over the last few decades, driven by the technological increase in computational power (Solomatine et al., 2008). DDM seeks an unbiased approach using raw data and real-world observations without explicit or prior information on the physical behaviour of the system, which could influence results based on omission or misunderstanding of environmental processes (Solomatine et al., 2008; Montáns et al., 2019). DDM can produce more accurate models in near or real-time using big data than conventional modelling techniques (Shen et al., 2019). As such, DMM can give an accurate picture of the system as it is, instead of how researchers expect it to be directly analysing big data in real-time. Nevertheless, understanding fundamental ecosystem processes before implementation is essential, as the potential omission of data describing a key process can be particularly problematic and result in inaccurate prediction outputs. The evolution of DDMs has stalled as ML techniques remain restricted to predicting rather than describing and investigating the underlying processes of model outputs (Lucas, 2020). Many popular ML approaches have a “black box” reputation, whereby models sacrifice transparency for increased prediction accuracy (Zhao and Hastie, 2021). Therefore, it is preferable to understand the mechanisms underlying models before considering ML techniques as tools for management applications (Schuwirth et al., 2019).

Given the popularity of implementing highly accurate ML techniques due to the increasing accessibility and availability of big data and the demand for more “transparent” machine learning explanations, there is interest in combining the exploratory benefits and predictive capacity of ML algorithms with a mechanistic understanding of process-based models (Charnock et al., 2020; Chibani and Coudert, 2020). DDM can be designed to alert users to previously overlooked correlations which can be explored further to understand if there are cause-and-effect processes at play within the ecosystem. Additionally, DDM can be used to harness big data to exploit the correlations in variables, allowing decision-makers to assign uncertainty thresholds for ecological processes that may lack information. (Willcock et al., 2018; Charnock et al., 2022). However, while this hybrid modelling approach has been attempted and applied in the last decade (Chau, 2006), there is still often a lack of big data to implement into these models, particularly biological data, which are more complex and less objectively interpretable than physics-based data (Marx, 2013). The complementarity of DDM and process-driven modelling may eventually result in a “best practice” approach to environmental modelling, assisting managers in effectively utilising and understanding data from an automated system. However, there have been recent attempts to “open the black box” in a number of biological fields such as genetics (Azodi et al., 2020) and medicine (Baselli et al., 2020; Poon and Sung, 2021) to create interpretable ML models. This is important in conservation science as ensuring the collection of appropriate data and understanding the driving ecosystem processes is important to effect change in the appropriate areas for managers. As computational power advances and big data becomes ubiquitous in all disciplines, ML’s ability to adapt continuously and quickly to changing environments may provide near real-time prediction of complex environmental processes with great accuracy.

Predictive models and adaptability

Predictive models can be used to make forecasts about future ecosystem states and can inform decision-makers by comparing alternative management strategies and quantifying uncertainties (Geary et al., 2020). Due to the wide variety of data analysis methods and tools, and the complexity of different monitoring projects, there is no single best practice for data analysis that can be suggested as an overarching solution. Choosing the most appropriate modelling approach depends on the management goals, requiring collaboration with modellers and managers to determine the most appropriate approach. (Araujo et al., 2020)

Training ML algorithms by reinforcement learning (RL) using real, raw data may better support adaptive management and agile decision-making relative to supervised or unsupervised training of machine learning algorithms (Figure 3). RL algorithms do not require a pre-defined training dataset and instead, interact directly with their environment to identify optimal decisions to achieve a “goal” by being either “rewarded” or “punished” for certain decisions (Sutton and Barto, 2018). RL algorithms have been used in the context of environmental management and conservation decision-making, however, due to the historic lack of empirical data and computational power, modelling using reinforcement learning

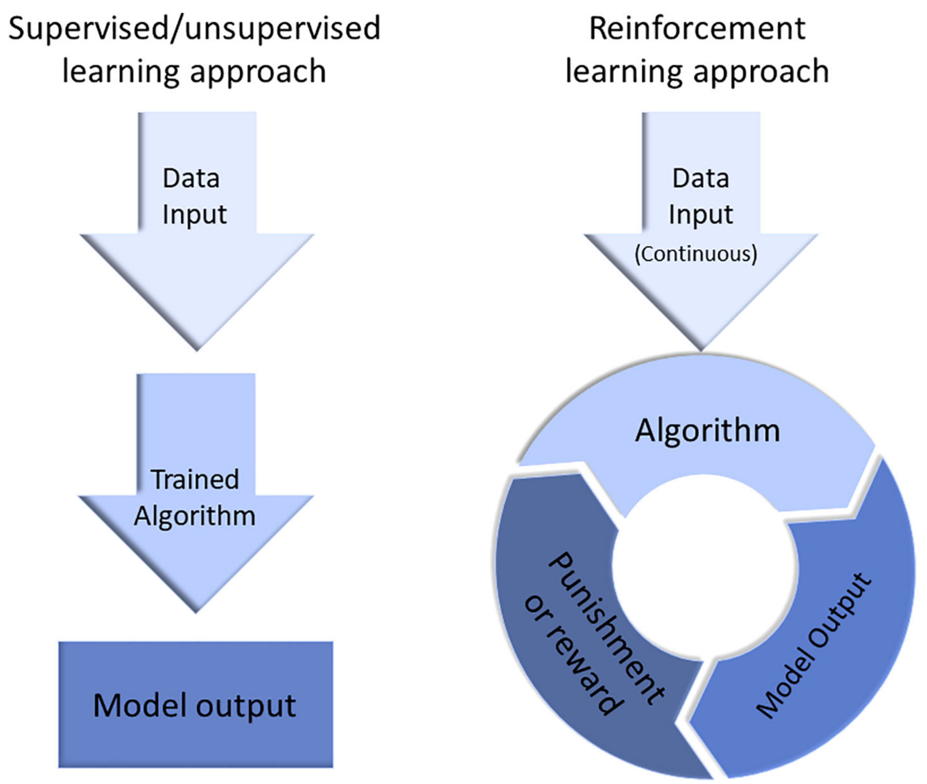

FIGURE 3
Traditional machine learning techniques improve prediction accuracy by incorporating more training data for the model to learn. Conversely, deep reinforcement learning allows models to improve by incorporating more data through their continued exposure to their environment and by rewarding or punishing correct and incorrect actions, respectively.

has previously been limited to using simulated data and theoretical approaches to management (e.g. Chades et al., 2007; Verma et al., 2018; Frankenhuis et al., 2019). However, the rise in computing power and increasing availability of big data means that RL can now be combined with artificial neural networks, i.e., "deep RL" to interact with real-world data and exploit the advantages of this training approach to assist in decision-making. In an automated monitoring system, deep RL can not only be used to optimise the autonomous nature of remote sensing networks at the data collection and transfer stages (Luong et al., 2019), but algorithms could also interact with continuous streams of real-world data (i.e. data-driven reinforcement learning) and predict future ecosystem states (the "goal"). If the model accurately predicts the variable of interest, which is validated by the continuous incoming data, it is "rewarded", if not, the algorithm is "punished", and so on.

Deep RL increases performance through continuous interactions with its environment, making it ideal for integration into long-term monitoring as it can adapt to change since its actions are not predetermined, unlike supervised learning. The ability to learn from continuous real-world data and adapt outputs accordingly may enable managers to predict near-term future ecosystem states and decision responses to provide effective solutions to real-world problems by integrating this knowledge and linking automated monitoring data, particularly with emerging biological big data, in causal relationships using management frameworks such as DPSIR (Sekovski et al., 2012; Tscherning et al., 2012; Rodríguez-González et al., 2017). This learning technique may give the much-needed empirical support to mechanistic frameworks which often face challenges in obtaining the required ecosystem state knowledge under the effect of potential management actions (Polasky et al., 2011). Furthermore, RL can support iterative and near real-time forecasting of management outcomes, thereby supporting agile decision-making for effective and quick management applications (Lapeyrolerie et al., 2021). This technology highlights the ability of AI to produce immediate, actionable solutions without introducing long-term threats to environmental systems (Nishant et al., 2020). However, the implementation of deep RL requires vast amount of data relevant to the modelling goal. Current research using RL modelling techniques including prediction of crop yield in agriculture based on raw data collected on environmental parameters in a semi-constrained environment, to create models that can create accurate outputs and learn from continuous data over multiple crop seasons (Elavarasan and Vincent, 2020). However further research is needed to test the scalability of these models in large, unconstrained marine environments over appropriate time scales, and what data is needed to achieve accurate model outputs.

Enabling and supporting decision making

To facilitate effective management, information gathered from automated monitoring must be efficiently transferred to decision-makers. A technological solution for information transfer, understanding, and interaction may come from a tailored and management-oriented user interface at the end of the automation pipeline (UI). A UI is a space where humans interact with machine processes and can be designed to be "user friendly" to assist interaction at an appropriate level of user understanding. For example, the popular web-based search engine Google has a UI designed to make information retrieval accessible to individuals with little to no computer training. Programming languages such as R have been utilised as an effective data visualisation tool and statistical analysis tool for large datasets (big data) in the last decade, increasing from 11% of ecological studies utilising R in 2008 to over 58% in 2017 (Lai et al., 2019). However, these require skill-specific coding knowledge that is not always shared by researchers and managers. Custom-built UI platforms, such as web applications, designed for environmental monitoring could provide managers with real-time information on the state and condition of their management area without the need for coding expertise. The UI could display key information for managers as data summaries, such as trends in animal abundances over time or if specific variables are nearing manager-defined thresholds, as well as providing its own suggestions from automated, data-driven decision making. Additionally, the use of AI algorithms can note areas with data deficiencies, like the citizen science, bird monitoring app eBird, recognises data-poor regions and gamifies data collection in these areas for users to improve the spatial balance of data collection (Kelling et al., 2013). However, the development of tailored software can incur high initial costs in proportion to project budgets and may require collaboration across different areas of expertise, including managers, software developers, modellers, and researchers (McClure et al., 2020). Integrating automated monitoring and UIs may be a useful tool for long-term monitoring and management programs, which otherwise can be troubled by issues with staff and leadership turnover, ongoing training costs, and loss of skill sets (Caughlan and Oakley, 2001; Likens and Lindenmayer, 2018). Informative data summaries and predictive outputs should be accessible to managers without extensive modelling expertise, including predictions of environmental change under different management scenarios that can also be displayed in the UI (Fer et al., 2021). As ML continues to demonstrate its applications in environmental technology (Lamba et al., 2019), increasing attention has been centred on maximising the integration and usability of technologies towards management-ready UIs that support decision-making by providing increased accessibility to relevant information. Examples of these collaborative efforts span from both land (e.g., https://www.globalforestwatch.org/) to oceans (https://reefcloud.ai/, https://allencoralatlas.org/ and https://datamermaid.org/). As AI can make the tracking of progress on quantitative conservation objectives easier, displaying and sharing data on these platforms can also make providing this information to managers easier.

Current challenges to implementing automated monitoring systems

While new technologies have been identified as valuable tools in environmental monitoring to assist conservation and management efforts for many ecosystems, there are still roadblocks to overcome for efficient and cooperative environmental management at the implementation level (Table 1). Democratisation of data requires efforts to make useful data accessible, including the effective management and appropriate storage for these data (Pimm et al., 2015); a challenge that requires global cooperation. Additionally, the implementation of mechanisms to evaluate the accuracy and precision of automatically collected and processed data are needed to provide tools for quality assurance and control of data provided by the automated system from the collection to processing phases. The cooperation and implementation of a standardised, systematic reporting framework for marine monitoring may assist in the transfer of knowledge between managers. Integrating AI technology with standardised reporting could allow managers to make informed decisions and share useful information to drive and improve management success (Eger et al., 2022).

Social factors may also act as a roadblock to the proliferation of automated monitoring. The reluctance or inability of groups to share data could slow global, or even local, cooperative research and impede quick and effective conservation efforts. This is why making useful data easily accessible is important for improving AI implementation in environmental research. Additionally, while the benefits AI has provided to businesses in many industries are increasingly evident, the hesitancy of in-house employees to implement AI initiatives will inevitably affect the efficacy of automated monitoring projects (Zhu et al., 2021). While potentially controversial, the outputs from AI-facilitated management suggestions can be highly informative and useful, as Araujo et al. (2020) found that predictions made by automated decision-making algorithms, on individuals' opinions about the fairness and usefulness of automated decision-making, ironically, were on or even better than

TABLE 1 Summary of areas of research that have substantial gaps and challenges in marine ecosystems that require further research to create useful tools to assist conservation management through automated monitoring facilitated by artificial intelligence.

	Process step	AI/Automation technology	Gaps	Challenges
Monitoring	Data collection	Cameras UAVs eDNA Remote sensing	•Collecting big data on animal response to restoration efforts across appropriate spatial and temporal scales	•New technologies may be prohibitively expensive: eg eDNA •Processing bottlenecks •Cost results in inappropriate monitoring designs implemented
	Data transfer	Edge computing, underwater networks, cabled observatories	•Scalability and feasibility of edge computing in marine environments	•Infrastructure is costly to implement •Marine-specific environmental challenges eg short transfer distance •Big data transfer and storage needs
	Data processing	Computer vision/Deep learning	•Scalability and accuracy of models to answer ecological questions by integrating deep learning model outputs •Investigating alternative solutions to marine-specific challenges such as varying water visibility •Automated sizing using stereo-cameras	•Limitations of small training datasets •Marine-specific environmental challenges •Cost of marine-related site accessibility restricting the breadth of studies eg boating and diving costs.
Evaluation and decision support	Data summary and analysis	Data visualisation	•Data-driven modelling for analysis of true "big data" from raw data inputs •Exploiting newly available capabilities of big data analysis	•Biases in big data collection can lead to misleading results •Requires the possible creation of new metrics and methods of data analysis
	Predictive models and adaptability	Data driven modelling and reinforcement learning	•"Opening the black box" for ML model interpretability •Reinforcement learning using continuous streaming of raw data	•ML model interpretability may be difficult depending on the complexity of the data input •RL is computationally challenging and expensive •Lack of 'true' big data to implement RL effectively
	Decision making support	Adaptable user interfaces	•Easily interpretable information *via* user interfaces to facilitate decision making	•Possibly expensive and outside project budget •May need ongoing maintenance and flexibility for adaptive management approach
Other	Social challenges	NA	•Education on AI technologies and capabilities •Appropriate upskilling of staff	•Wariness of new technology and implications for jobs •Possible high initial costs associated with upskilling staff
	Centralisation of data and data sharing	Data integration	•Creation and implementation of standardised reporting frameworks •Democratisation of data	•Lack of global-cooperative efforts in standardisation due to varying opinions and resources •Organisation intellectual property rules and lack of centralised databases and frameworks for effective data sharing

human experts when given only data on an individual's general characteristics.

While these challenges highlight current roadblocks to implementation, there are other considerations once these automated systems begin to be utilised. It is important to note the detriments of heavy reliance on automated systems, particularly for quality assurance and control. There is already a societally-normalized trust in AI that many already experience in our day-to-day lives from phone applications to household appliances (Bedué and Fritzsche, 2021). However, the benefits that automation can provide often outweigh the risks which can also be mitigated by accounting for perceived risks. For example, AI has been implemented to detect a number of cancers in patients (Hoshyar et al., 2011; Kudva et al., 2018; Espinosa et al., 2020). However, the risk of the machine returning a false negative for a patient can have dire consequences for the individual. By factoring this into the automation process, in which the algorithms are set to have higher recall than precision (higher false positives are generated instead of false negatives), the risk of missed pathologies is reduced (Livingstone and Chau, 2020). These technologies, while useful tools for assistance and increasing ecological knowledge, do not replace the many facets that need to be considered by managers in the decision-making process.

Conclusion

As funding for long-term monitoring projects remains scarce, the cost of purchasing, implementing, and running AI technology continues to decrease, making automation an attractive alternative for conservation management in marine ecosystems. We have shown that automated monitoring to obtain big data may assist in broadening our understanding of these relatively inaccessible marine ecosystems. Coupled with sophisticated machine learning algorithms to analyse data, automated monitoring can provide managers with a comprehensive, cost-effective, and constant supply of accurate information for long-term monitoring and optimal, adaptive management decisions, particularly where systems are changing due to anthropogenic influences. Despite the current technological and social challenges facing the implementation of AI and automated systems in management, the unprecedented amount of data becoming available, coupled with advances in ML over the last few years can provide managers and researchers with the tools to create accurate and agile predictions. This will ensure appropriate and successful management outcomes with the aid of additional analysis and decision support applied to an adaptive management framework. However, there are still many areas of research that need further investigation on the feasibility and scalability of these technologies before they are implemented into fully end-to-end automated monitoring systems. Despite this, "semi-automated" approaches where individual technologies can be adopted at different stages is currently feasible and may assist in immediate increases in information. The more accessible and pervasive use of technology can encourage uptake and improve management outcomes and overall understanding of marine environments and ecological processes for conservation.

Author contributions

ED led the conceptualisation and writing of the manuscript, with input from all authors. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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