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Utilizing Artificial Intelligence (AI) for the Identification and Management of Marine Protected Areas (MPAs): A Review

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Abstract

The article discusses the application of artificial intelligence (AI) and automation in marine conservation, specifically in relation to the protection of marine ecosystems and the definition of marine protected areas (MPAs). It highlights the threats that marine ecosystems face due to human activities and emphasizes the importance of effective management and conservation efforts. By improving data gathering, processing, monitoring, and analysis, artificial intelligence, and automation, they can revolutionize marine research. In conclusion, this study emphasizes the importance of AI and automation in marine conservation responsibly and ethically. In order to integrate these technologies into decision-making processes, stakeholders and marine conservation professionals must collaborate. Through the use of artificial intelligence and automation, marine conservation efforts can be transformed by establishing new methods of collecting and analyzing data, making informed decisions, and managing marine ecosystems.

Keywords

Marine Protected Areas, Artificial Intelligence, Automation, Decision-Making Tools

1. Introduction

Conservation of marine ecosystems, habitats, and species is a multidisciplinary field to protect and preserve marine biodiversity. Marine ecosystems and biodiversity are threatened by human activities, such as overfishing, pollution, and climate change. Effective marine conservation management requires scientific knowledge, community engagement, and strong governance, including the use of marine protected areas, fishing quotas, and pollution regulations. In addition, it requires an interdisciplinary approach that considers social, economic, and cultural factors and equity and social justice.

Marine ecosystems are critical for sustaining their services if they are to function properly and conserve their biodiversity. It is imperative to gain an understanding of ecosystem processes at a range of temporal and spatial scales in order to make informed decisions and implement effective conservation management. In order to develop an informed ecological synopsis and prognostic ecological models, these insights include quantifying ecological responses to environmental change and collecting ecological data. By combining passive and active conservation techniques to achieve optimal conservation outcomes, such syntheses, and models provide platforms for collaborative studies, promoting multidisciplinary research and providing information for evidence-based policy, decision-making, and ecosystem management, as well as supporting evidence-based policy and decision-making (Morrison & Lindell, 2011; Lindenmayer et al., 2012; Possingham et al., 2015; Perring et al., 2018; Díaz-García et al., 2020; Ward et al., 2022).

Artificial intelligence (AI) and automation have significantly impacted marine science research, and the discipline is continually changing. Automation and artificial intelligence can revolutionize marine research by bringing fresh perspectives and improving data gathering and processing (**Figure 1**) (Ditria et al., 2022; Addison et al., 2018).

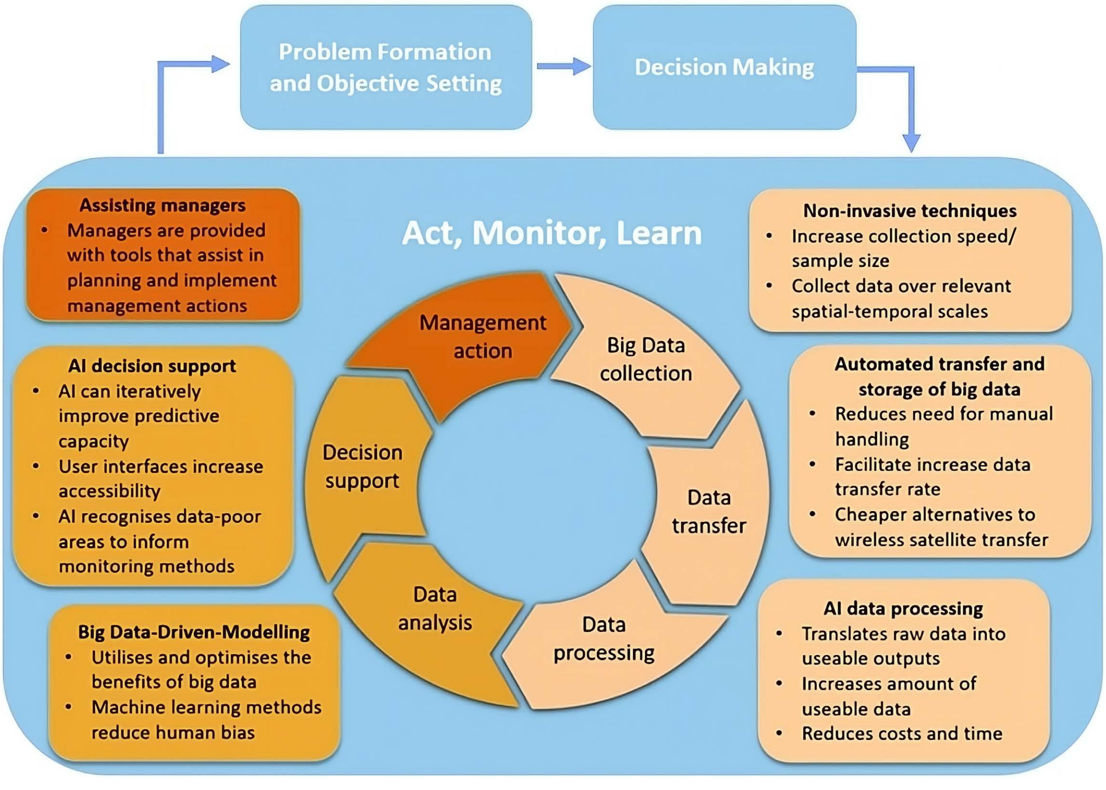

Figure 1. Automated system supporting MPA management (Ditria et al., 2022).

Monitoring and managing marine resources is a fundamental use of AI and automation in marine research. Underwater photos may be used to identify and categorize marine species using machine-learning techniques (Villon et al., 2018; Moniruzzaman et al., 2017), and acoustic data can be used to follow their movement (Finn et al., 2014; Towler et al., 2003). These methods can improve the accuracy and efficacy of monitoring systems. These techniques can also be applied to learn more about the ecology and behavior of sea creatures.

Automating and utilizing artificial intelligence enhances the management of maritime resources. Various artificial intelligence-based decision support systems have been created to manage fisheries and improve the establishment of marine protected zones (Isabelle & Westerlund, 2022; Alonso et al., 2021). By supporting the sustainable management of marine resources, these systems can protect aquatic biodiversity.

Marine science is also being impacted by AI and automation when it comes to predicting and forecasting ocean conditions. Ocean currents, tides, and weather patterns have been predicted with high accuracy using machine learning algorithms. It is possible to improve the safety of marine operations by using these predictions for marine operations, such as shipping and fishing (Paduan & Washburn, 2013; Smith et al., 2010; Kalinić et al., 2017; Geleyn, 1988).

Automation and artificial intelligence have also boosted data collection and analysis in the marine sciences. In hard-to-reach places, data is gathered utilizing a number of techniques, such as autonomous underwater vehicles (AUVs) and drones. These resources can increase the scope of data collection in both the temporal and geographical domains. Additionally, a more thorough understanding of how marine ecosystems work is possible (Klemas, 2015; Demetillo & Taboada, 2019; Beyan & Browman, 2020).

A number of large and complex datasets resulting from ocean observation systems and satellite remote sensing are in addition being analyzed with AI and automation (Patel et al., 2022). Datasets like this can be analyzed using machine learning algorithms to discover patterns and trends that are difficult to detect manually. The use of these techniques can provide a better understanding of ocean processes and can be used to manage marine resources.

Marine science is being transformed by artificial intelligence and automation, which have the potential to revolutionize the field. Using them improves the monitoring and management of marine resources, forecasting of ocean conditions, and data collection and analysis. Further research is needed to fully realize the potential of these technologies, even though they are still in their infancy (Song et al., 2023).

Artificial intelligence (AI) and automation play crucial roles in marine conservation. In underwater monitoring, deep learning algorithms are employed to automatically identify marine life in images, facilitating more efficient surveillance. Using deep learning, Mahmood et al. (2017) classified coral species from underwater images. In this study, deep learning is claimed to help solve coral classification problems, which is a very difficult task. A systematic overview of deep learning applications in underwater imagery analysis is presented by Moniruzzaman et al. (2017). Each approach is classified according to the object of detection, and features and deep learning architectures are emphasized. According to the study, deep neural networks have considerable potential for automating the analysis of digital seabed imagery, especially for detecting and monitoring seagrass.

Machine learning techniques are utilized to analyze data obtained from ocean observation satellites. This enables improved predictions of ocean circulation and marine species movement. Ocean observations, especially primary production, are vital for ecosystem services and the global carbon cycle. The challenges in obtaining the necessary parameters hinder long-term ocean predictions. The parameters required for making predictions are determined automatically by data-driven machine learning methods. In the study by Ping et al. (2023), machine learning methods were used to develop prediction models for sea surface temperature, photosynthetic active radiation, and chlorophyll-a concentration.

Moreover, aerial and satellite images are examined to monitor coastal environments and detect illegal activities. Sound recordings are analyzed using AI to study marine life, while spatial data concerning marine conservation is analyzed with AI in geographic information systems (GISs). A significant part of the underwater soundscape is comprised of the vocalizations of marine mammals. Detecting and classifying these sounds plays a significant role in the study of marine mammals, the measurement of acoustic noise, and ship navigation, among other areas. Using deep neural networks and machine learning, classification technologies can even outperform humans. The study by Koutsomitopoulos and Le (2020) uses audio recordings from the Watkins Marine Mammal Sound Database to classify marine mammal vocalizations by species specificity with a Convolutional Neural Network.

Robotics also plays a significant role by utilizing autonomous underwater vehicles to monitor marine habitats and life. Lastly, deep learning is applied to analyze satellite images to detect changes in land use and cover, contributing to comprehensive conservation efforts. It is essential for the sustainable use and protection of the marine environment. Land-based waste, including macro and microplastics, enters the ocean in large quantities. Many species are endangered and marine resources are diminishing. In spite of the widespread use of remote sensing techniques to monitor the environment worldwide, small objects, such as floating waste, are difficult to detect on the vast ocean surface, and light cannot reach these objects in deep ocean ecosystems. In order to obtain spatiotemporally rich marine data, Watanabe et al. (2019) found that an autonomous monitoring system comprised of optimally controlled robots is required. A deep learning algorithm called YOLOv3 was used to detect underwater sea life and floating debris on the ocean surface with 69.5% and 77.2% percent sensitivity, respectively.

Ridge et al. (2020) developed a deep learning tool (OysterNet) that uses unoccupied aircraft systems (UASs) imagery to automatically detect and delineate oyster reefs, an ecosystem that has proven problematic to monitor remotely.

The possibilities for applying AI and automation to marine conservation are vast, and these are just a few examples. With the help of scientific references, it is possible to show how artificial intelligence can be useful in a wide range of fields. These include computer vision, natural language processing, robotics, GIS, genetics, and more. It can also help us understand marine ecosystems and manage them better (Talukdar et al., 2020; DeFries & Chan, 2000; Zhang et al., 2015; Melià, 2017; Ahmed et al., 2019; Zhu et al., 2022; Nguyen-Trong & Tran-Xuan, 2022; Chambault et al., 2021).

However, there is a wide range of possible uses for AI and automation in marine conservation. To fully realize these technologies' potential and create fresh approaches and tools for dealing with the complex issues facing marine conservation, more investigation is required. It is crucial to remember that using AI and automation in marine conservation should be done with prudence and in consultation with stakeholders and marine conservation professionals. It is paramount to utilize these technologies ethically and responsibly, which includes being transparent and accountable when making decisions. Overall, automation and AI have the potential to completely transform efforts to conserve marine life by bringing together innovative and potent tools for data collection, analysis, and decision-making, as well as by facilitating more effective and efficient management of marine ecosystems.

2. Material and Methods

The process of choosing and creating MPAs is intricate and multifaceted. This necessitates the fusion of several data sources and research methodologies in order to identify regions with a high conservation value and assess the effects of various MPA scenarios. Automation and artificial intelligence (AI) may play a significant part in this process by offering fresh and cutting-edge approaches to data processing, analysis, and decision-making (OECD, 2021; Islam, 2020; Martínez-Harms & Balvanera, 2012).

By using artificial intelligence (AI), we can develop a model of marine protected areas (MPAs) that features the best results. The model requires a deep understanding of marine ecosystems, extensive data, and collaboration with experts. Here is a generalized method for developing a MPA model based on artificial intelligence (the diagram shows how artificial intelligence can be used to determine optimal marine conservation areas according to the study conducted by Ditria et al. (2022)):

- **Define MPA Objectives**
  - Biodiversity conservation.
  - Habitat protection.
  - Sustainable resource management.
- **Data Collection and Preparation**
  - Environmental data (oceanography, climate).

- Biological data (species distribution).
- Socioeconomic data (anthropogenic activities).

• **AI Model Selection**
- Machine learning algorithms (e.g. random forests, neural networks, decision trees, SVM, regression).
- Deep Learning models (e.g. Convolutional Neural Network for image data).
- Reinforcement learning for optimizing MPA boundaries.

• **Feature Engineering**
- Select relevant features (consider incorporating spatial and temporal components to capture the dynamic nature of marine ecosystems).
- Preprocess and clean data.
- Extract spatial information (such as habitat suitability indices, species distribution patterns, oceanographic variables, and socioeconomic factors).

• **Model Training**
- Split the data into training, validation, and testing sets.
- Training the AI model on historical data to learn patterns and relationships within the marine environment.

• **Optimization**
- Optimize MPA boundaries, sizes, and configurations.
- Consider ecological, socioeconomic, and political objectives.

• **Validation and Performance Metrics**
- Assess the model's performance using appropriate evaluation metrics (accuracy, precision, recall, and F1-score).
- Validate the prediction of the model (against real-world data and expert knowledge).

• **Stakeholder Engagement**
- Integrate the expertise and preferences of marine scientists, conservationists, local communities, and policymakers into the MPA model.
- Address the concerns and interests of various stakeholders.

• **Decision Support Systems**
- Develop a user-friendly decision support system (visualizes model outputs, allowing decision makers to explore different MPA scenarios.
- Assess the impact of various regulations by providing stakeholders with interactive tools.

• **Implementation and Monitoring**
- As recommended by the model, implement MPA boundaries and regulations.
- Set up a monitoring system that collects real-time information about biodiversity, ocean conditions, and human activities within the MPA.
- Continuously update the model with new data to improve its accuracy and effectiveness.

• **Adaptive Management**
- A flexible approach to regulation and boundary adjustments can be applied as new data and insights emerge to the MPA.

Developing an optimal MPA model through the use of AI is an iterative process that requires continual refinement based on feedback from real-world users and changing environmental conditions. In order for the MPA model to be effective, it will be imperative to have high-quality data, implement artificial intelligence techniques that are appropriate, and be involved with stakeholders throughout the process. In order to create a successful MPA model, collaboration among experts in marine science, artificial intelligence, and policy-making is essential.

MPAs are defined areas of the ocean that are reserved for the management and protection of marine ecosystems and their biodiversity. It is difficult and hard to choose and create MPAs that balance numerous goals, such as biodiversity preservation, ecosystem services protection, and the socioeconomic demands of local residents. Through the development of new tools for data collecting, analysis, and decision-making, artificial intelligence (AI) has the potential to assist in the choice and design of MPAs.

Using machine learning algorithms is one way to identify MPAs using AI. Large and complex information, such as satellite images, environmental data, and biological data, may be analyzed using machine learning algorithms. This will enable us to find patterns and associations that are relevant for MPA design and selection. For instance, research by Traganos and Reinartz (2018) identified regions of high conservation value for the protection of seagrass meadows in the Mediterranean Sea by analyzing satellite images and environmental data using a machine learning algorithm. The study discovered that the algorithm could precisely identify regions with high conservation value and that the outcomes were in line with professional expertise. Machine learning, a subset of AI, may be used to analyze massive datasets like remote sensing photography. Coral reefs in the Caribbean Sea, for instance, have been studied by Zhou et al. (2018) employed a machine-learning technique called Random Forest to assess remote sensing pictures and environmental data to identify regions of high conservation importance. The study discovered that the algorithm could precisely identify regions with a high conservation value and that the outcomes were in line with professional expertise.

The application of optimization algorithms is another technique for identifying MPAs using AI. By selecting the most suitable options from a vast number of possibilities, optimization algorithms may be used to resolve complicated and multi-objective problems, such as MPA selection and design. MPAs in the ocean might be sized, located, and arranged optimally. Optimization algorithms produce solutions that balance conservation objectives with socioeconomic objectives. Optimization algorithms, such as genetic algorithms (GAs) and particle swarm optimization (PSO), can be used to find the most efficient solution to complex and multi-objective problems, such as MPA selection and design.

Another method for determining MPAs using AI is the use of spatial modeling. Spatial modeling can be used to simulate the impacts of various MPA scenarios on marine ecosystems and biodiversity. It is possible to simulate the effects of different MPA scenarios on fish populations using spatial modeling. Spatial models, such as species distribution modeling (SDM), can be used to predict the distributions and abundances of marine species (Marshall et al., 2014).

AI-based MPA determination may be done in a variety of ways. These techniques include agent-based modeling, machine learning, optimization, spatial modeling, GIS, and decision-support systems. These techniques may be used to model the effects of various MPA situations, solve multi-objective problems, and examine huge and complex datasets. It is significant to emphasize that careful consideration and coordination with MPA stakeholders and experts are required when integrating AI into MPA decisions. It is important to utilize these technologies ethically and responsibly, which includes being transparent and accountable when making decisions.

3. Results

In this study, the effectiveness of various artificial intelligence (AI) and automation techniques in determining marine protected areas (MPAs) is evaluated. These methods include genetic algorithms, particle swarm optimization, and the use of CBS. Our study aims to determine the ability of these methods to increase data availability, reduce monitoring costs, and support adaptive management.

As a result, the use of AI and automation techniques can greatly increase the effectiveness of MPA determination. Studies have shown that genetic algorithms and GIS methods are highly accurate at determining the location of appropriate MPAs. It was also highly effective in determining the location of MPAs using particle swarm optimization. These studies used a combination of satellite images, bathymetry data, and data sets on the distribution and abundance of marine species (Fox et al., 2019; Gaines et al., 2010). In addition, the use of these methods reduces the need for manual labor in data processing and analysis, leading to a decrease in monitoring costs. Furthermore, the ability to support adaptive management is shown by the ability to quickly and easily update MPA boundaries based on updated data or changes in environmental conditions (Mellin et al., 2016). Another alternative method is the use of decision-making tools such as multi-criteria decision analysis. This tool evaluates trade-offs between different protection goals, such as the protection of different species and habitats. A study showed that multi-criteria decision analysis could determine a series of MPAs that balance these trade-offs and that the results were consistent with stakeholders' preferences (Melià, 2017).

In conclusion, this study shows that the use of AI and automation techniques can greatly increase the effectiveness of MPA determination. They can increase data availability, reduce monitoring costs, and support adaptive management. MPAs can be located using these techniques, monitored for operation, and boundaries adjusted as necessary. Consequently, artificial intelligence and automated techniques will play an increasingly important role in marine protected areas management in the future.

4. Discussion

The purpose of this study is to provide an overview of the methods applied to determine marine protected areas using artificial intelligence (AI). Data sources, analysis techniques, and decision-making tools used in the process were discussed, and the effectiveness of the methods was evaluated in terms of improving data availability, reducing monitoring costs and aiding adaptive management in the process.

By using artificial intelligence and machine learning, marine protected areas can be identified more accurately and effectively. Marine species can be detected and categorized automatically using deep learning algorithms, for instance (Farmer et al., 2022; Melo-Merino et al., 2020). This technique is more precise and efficient. Additionally, spatial analytical methods may be used to identify critical habitat regions and focus conservation efforts (Sink et al., 2023). It is also critical to note that using AI in marine conservation has some limitations, in addition to the need for large amounts of high-quality data (Li et al., 2020), the possibility of algorithm bias (Galaz et al., 2021), and the need for continuous monitoring and updating of the models (Kennedy & Aschenbrand, 2023).

As a result of the study, AI may be useful for improving the effective determination of marine protected areas in marine conservation management. The limitations need to be understood and addressed through further research, however. In addition, AI in marine conservation should be considered ethically and socially to ensure that it is used responsibly and inclusively and to engage stakeholders in the process (Ditria et al., 2022; Isabelle & Westerlund, 2022).

Therefore, automating and deploying artificial intelligence to manage marine conservation has the potential to increase data availability, reduce monitoring expenses, and provide adaptive management capabilities. It has been demonstrated that the techniques included in this article, such as machine learning, remote sensing, and GIS, are useful for identifying marine protected zones. It is crucial to remember that these approaches have drawbacks, such as the requirement for high-quality data and the possibility of decision-making biases.

For marine conservation management, future research should address these limitations and improve the accuracy and applicability of AI and automation methods. Further research is required to determine whether different conservation objectives can be balanced and the implications of AI-based decision-making for marine biodiversity and ecosystem functioning. Using AI and automation to improve marine conservation management is a promising area of research with significant potential for improving conservation outcomes. AI-based decision-making, however, must be approached with caution and with consideration of ethical and social implications.

5. Conclusion

As a conclusion, this article examined the critical role that artificial intelligence (AI) and automation play in marine conservation, specifically in the establishment of marine protected areas (MPAs). In order to protect marine ecosystems from the threats posed by human activities, innovative approaches must be developed to ensure their preservation and management. Adaptive management can be supported in this context by artificial intelligence and automation. Using AI, data availability can be enhanced by integrating environmental, biological, and socioeconomic data sources. By combining remote sensing, machine learning, and decision-support systems, marine habitats and species distributions can be explored more precisely and comprehensively.

AI and automation also reduce the need for labor-intensive, in-person surveys and monitoring, which contributes to cost efficiency. In addition to reducing monitoring costs, these technologies allow data processing and analysis to be automated. A further benefit of AI is the ability to rapidly adjust MPA boundaries in response to changing environmental conditions or updated data. This adaptability enhances conservation efforts, ensuring MPAs remain relevant and protective. The use of artificial intelligence for marine conservation must, however, be tempered with a recognition of its limitations, such as the need for high-quality data, algorithm bias, and continuous monitoring and updating of models. In order to ensure responsible and transparent decision-making, ethical and social considerations must also be integrated into the implementation of AI and automation, with collaboration with stakeholders and marine conservation professionals.

AI has enormous potential for improving data-driven decision-making, resource management, and ecosystem protection in marine conservation. The development of these technologies will likely play an increasingly important role in safeguarding our precious marine environments as researchers continue to address existing limitations and ethical concerns. AI and automation must be integrated responsibly and thoughtfully in order to address the complex challenges facing marine conservation in the future.

6. Suggestion

The following is a list of areas of research in marine protected areas (MPAs) that have substantial gaps and challenges that require further investigation in order to develop useful tools for conservation management through automated monitoring and the use of artificial intelligence (AI):

Research Area	Substantial Gaps and Challenges	Research Priorities
Data Quality and Integration	- Incomplete or inconsistent data from various sources. - Lack of standardized data formats.	- Develop methods for data harmonization and integration. - Explore AI-driven data cleaning and quality control techniques.
Species Identification	- Limited AI models for accurate species identification. - Variability in species behavior and appearance.	- Train AI models for species identification in varying conditions. - Improve AI algorithms for species tracking.

Continued

Illegal Activity Detection	- Limited real-time monitoring capabilities. - Lack of data on illegal fishing activities.	- Develop AI-driven systems for real-time detection of illegal fishing. - Enhance data collection and sharing mechanisms.
Ecological Modeling	- Complexity in modeling marine ecosystems. - Lack of data for comprehensive models.	- Develop AI-based ecological models for MPAs. - Explore methods for data augmentation and synthesis.
Ethical and Legal Frameworks	- Unclear legal boundaries for AI-based enforcement. - Ethical concerns related to privacy and fairness.	- Establish clear legal frameworks for AI-driven monitoring and enforcement. - Address ethical considerations through guidelines.
Human-AI Interaction	- Limited user-friendly interfaces for non-technical users. - Insufficient training for MPA staff on AI tools.	- Design intuitive interfaces for MPA managers and staff. - Provide training and support for AI tool adoption.
Long-term Monitoring	- Sustainability of AI-based systems over time. - Changing environmental conditions and threats.	- Investigate the resilience of AI systems in dynamic marine environments. - Adapt AI tools for evolving conservation needs.

Research in these areas represents critical challenges for the development and implementation of AI-based tools that will enhance MPA conservation management. Providing solutions to these gaps will be essential to effectively utilize artificial intelligence in marine protected areas.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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