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Machine learning, eDNA and citizen science in monitoring and assessing biodiversity and invasive alien species at sea

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This research outlines the integration of machine learning, citizen science, environmental DNA (eDNA), and other emerging technologies to enhance marine biodiversity and invasive alien species monitoring, discussed during a summer school organized by several European projects in June 2025. Furthermore, monitoring approaches are increasingly complemented by remote sensing, drones, and machine learning to expand spatial coverage and improve data processing. Machine learning supports species identification across taxa through deep learning and other methods, underpinned by robust validation protocols. Frameworks such as Essential Biodiversity Variables (EBVs) and Essential Ocean Variables (EOVs) standardize data collection and interpretation, enabling hypothesis-driven monitoring and global synthesis. Computer vision models (e.g., YOLO, Mask R-CNN) and transfer learning further facilitate species identification required by EBVs. Citizen science initiatives such as iNaturalist and MINKA combine machine learning-assisted identification with expert validation, substantially broadening biodiversity monitoring. However, spatial biases and limitations persist, particularly for cryptic and deep-sea taxa. For invasive species, technologies like autonomous vehicles and eDNA sampling enhance early detection. The CIMPAL+ framework supports ecosystem-based management by assessing cumulative impacts of non-native species. Overall, these tools enhance monitoring efficiency and inclusivity but require ethical oversight, standardized protocols, and interdisciplinary collaboration to ensure scientific integrity and policy relevance.

KEYWORDS
citizen science, eDNA, imaging, machine learning, marine management, artificial intelligence, essential biodiversity variables

1 Introduction

For decades, marine monitoring has supported managers in decision making (Danovaro et al., 2016; Mack et al., 2020). However, in the last three to four years, some research initiatives have advanced our capacity to monitor and assess the ocean with emerging innovative tools, approaches and methods, such as environmental DNA (eDNA), drones (aerial and submarine), imaging, modelling, etc. (Borja et al., 2024a). Despite these advances, the climate and biodiversity crises are intensifying, calling for more powerful tools to monitor, analyze, and assess ocean health across vast marine areas.

Remote sensing has been increasingly used to cover large ocean areas, providing valuable data for decision-makers on water quality (Mohseni et al., 2022) and biodiversity (Muller-Karger et al., 2018a), sometimes in combination with eDNA approaches (Yamasaki et al., 2017). Despite these advances, repeated monitoring over extensive areas, necessary for early detection of non-indigenous species (NIS), still requires *in situ* sampling using traditional approaches for accurate biodiversity assessment (Magliozzi et al., 2021). NIS are defined as species that have spread beyond their natural biogeographical range to new regions with human activities (Essl et al., 2018). Within NIS, invasive alien species (IAS) are defined as those "whose introduction or spread has been found to threaten or adversely impact upon biodiversity and related ecosystem services" (European Union, 2014). To achieve such extensive coverage of NIS and IAS monitoring, the use of citizen science is rapidly growing, with promising results (Baker, 2016; Pocock et al., 2018; Garcia-Soto et al., 2021).

On the other hand, technological development provides large datasets, being increasingly challenging to store and process; however, machine learning has recently facilitated marine monitoring (van der Plas et al., 2025) and improved data accessibility (Borja et al., 2025). This development enhances data availability and can enable informed decisions that promote ocean sustainability (Borja, 2025). Currently, the term machine learning is widely used for models that make predictions based on patterns in training datasets (e.g. image classification), whereas the term generative artificial intelligence (GenAI) refers to the creation of text or images that resemble human work but allow for more 'creative leeway'. There lies further risk of erroneous content, making GenAI less suitable/more controversial for scientific applications, while machine learning is more widely accepted in scientific research due to established knowledge about robust model building, validation and verification with ground truth (Fernandes-Salvador et al., 2026).

In this context, six European projects (GES4SEAS, OBAMA-NEXT, GuardIAS, BioBoost+, ANERIS, and POMP) joined forces in a summer school held in San Sebastián (Spain), from 3 to 5 June 2025 (Figure 1, Table 1). It was attended by 50 participants from 19 countries, including MSc and PhD students, post-doc and senior researchers, members from national agencies, industry, consultants and municipal counsellors. The objective was to review and discuss, with the attendees, the use of citizen science and machine learning in monitoring and assessing marine biodiversity (including IAS), to support managers and policy-makers in taking informed decisions.

This manuscript presents the status of the methods reviewed during the school and discusses the progress they represent towards

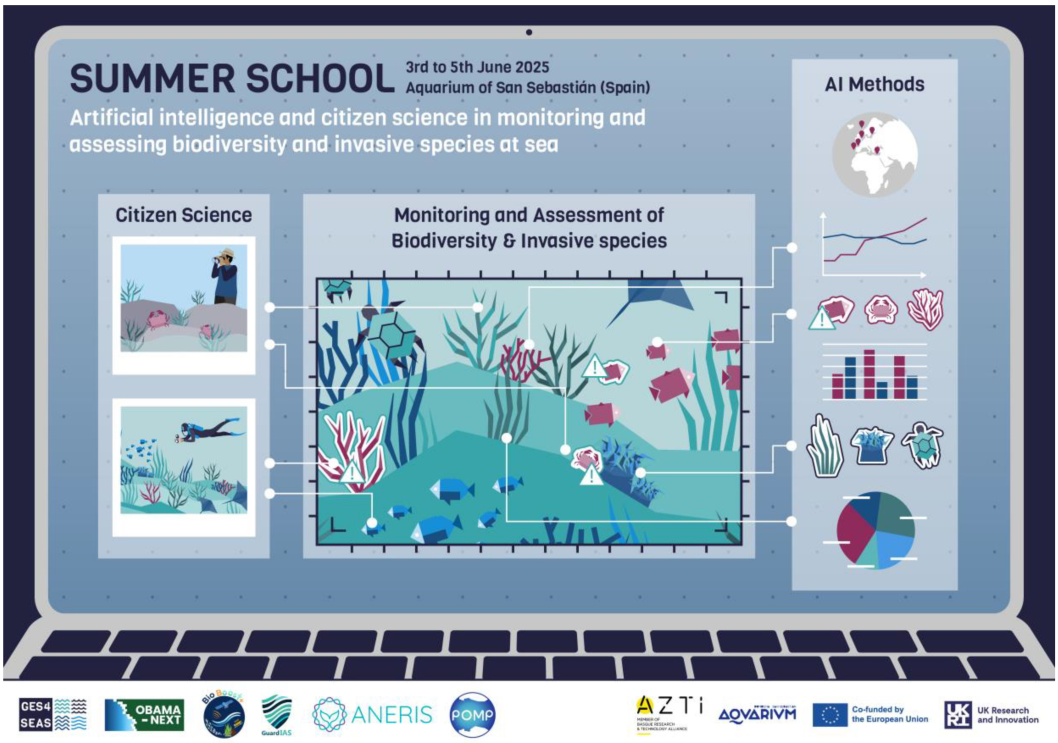

FIGURE 1
Infographics of the summer school organized by six Horizon Europe projects in San Sebastián (Spain), in June 2025.

TABLE 1 Summary of the six European projects organizing the summer school, with a short description of their objectives and main topic addressed.

Acronym	Web page	Duration	Main objective	Main topics addressed
GES4SEAS	https://www.ges4seas.eu/	2022–2026	Assess and achieve Good Environmental Status of seas under cumulative human pressures	Marine monitoring, cumulative pressures, ecosystem status, MSFD, biodiversity
OBAMA-NEXT	www.obama-next.eu	2022–2026	Deliver next-generation tools for marine biodiversity observation and monitoring	Biodiversity monitoring, eDNA, sensors, data products, ecosystem mapping
GuardIAS	https://guardias.eu/	2025–2027	Prevent and manage aquatic invasive alien species	Invasive species, AI detection, early warning, biosecurity, monitoring systems, citizen science
BioBoost+	https://bioboostplus.eu/	2023–2026	Boosting the frequency and scale of marine biodiversity monitoring using digital imagery and artificial intelligence	AI, digital imagery, automated monitoring, ecosystem assessment, data integration
ANERIS	https://aneris.eu/	2023–2026	Build next-generation marine sensing technologies and infrastructures	Marine sensing, genomics, bio-optics, research infrastructures, data systems, citizen science
POMP	https://pomp-project.eu/	2023–2026	Improve integrated ocean monitoring and modelling	Ocean monitoring, platforms, modelling, forecasting, environmental data, citizen science

improved management of European seas and beyond. The methods were selected by the six projects organizing the school, which are being investigated by them, bringing the most recent progress to the debate. This can be a limitation on generalizability, but since they represent the most recent research in these topics, it could be a good departing point on the state-of-the-art. The manuscript is divided into four sections: (i) emerging technologies to monitor marine biodiversity (e.g. eDNA, citizen science, machine learning); (ii) application examples of emerging technologies (e.g. machine learning in imaging and species identification so-called computer vision, active engagement of citizens in monitoring, integrating machine learning and citizen science, use of smartphones); (iii) using biodiversity data in interpreting and assessing impacts (e.g. in using essential biodiversity variables and using CIMPAL+ (Cumulative IMPacts of invasive ALien species) for IAS assessment (Chiappi et al., 2025)); and (iv) a discussion and future directions, outlining the next steps in monitoring and assessing marine biodiversity and IAS using these approaches. Sometimes, the sections address general marine biodiversity monitoring (all taxa), and others only focus on IAS, as target taxa.

2 Emerging technologies to monitor biodiversity in the ocean

2.1 Monitoring biodiversity

Monitoring marine biodiversity, including early detection of NIS and IAS, has relied on intertidal and underwater visual surveys, fisheries data, benthic sampling, and port or marina monitoring (Katsanevakis et al., 2012; Ulman et al., 2017; Tait et al., 2023). While effective, these surveys are costly and time-consuming (Ahmed et al., 2022), with SCUBA-diving surveys further constrained by time, depth, and safety, and are often limited in spatial and temporal coverage (Ditria et al., 2022). In addition, there are limited resources available for systematic surveys (Rogers et al., 2023). Such limitations have driven the adoption of emerging technologies (e.g. eDNA, machine learning) and participatory approaches (e.g. citizen science).

Advances in robotics now allow remotely operated (ROV) and autonomous underwater vehicles (AUV) to survey deeper and more hazardous habitats with high-resolution imaging (Piechaud et al., 2019; Tait et al., 2023). State-of-the-art AUVs can map large seafloor areas even in complex environments, featuring capabilities such as high-resolution cameras, terrain following and obstacle avoidance, streamlined user interface, increasingly assisted by computer vision for real-time identification (Katsanevakis et al., 2024). Robotic detection of small or cryptic species can be less reliable, however ongoing developments in automation and computer vision are steadily improving their efficiency (Tait et al., 2023; Katsanevakis et al., 2024).

Remote sensing has also expanded monitoring capacity by offering broad spatial coverage and frequent updates. For example, Roca et al. (2022) successfully mapped the distribution of the invasive alga *Rugulopteryx okamurae* in shallow waters using drones and satellites. Still, water depth and turbidity limit the application of remote sensing, and spectral similarities between non-native and native species demand careful field validation.

Among recent breakthroughs, eDNA stands out for its sensitivity and relevance for early warning on new IAS introductions, being analyzed in Section 2.2. Other innovations include passive acoustic monitoring, which uses species-specific sound signatures to detect specific invaders (Parsons et al., 2022). Many marine animals produce species-specific sounds, a fact well known for cetaceans and also documented in certain fish and invertebrates (Ladich, 2019). Recent research projects are exploring the potential of species-specific acoustic signatures as a methodological tool for detecting and monitoring NIS and IAS (Katsanevakis et al., 2024). To date, passive acoustics has seen limited application to IAS, partly because the "vocabulary" of sounds for most invasive taxa is not established (Parsons et al., 2022). Current efforts aim to compile a library of underwater sounds ("Global Library of Underwater Biological Sounds") and to link sounds to known species via simultaneous audio and video recording (Parsons et al., 2022; Katsanevakis et al., 2024). Once confirmed, sound signatures are available, and machine learning can be trained to automatically recognize them in continuous audio streams. Early studies have applied machine learning to animal sound classification with promising results (Huang et al., 2009; De Camargo et al., 2017), suggesting that an automated acoustic early-warning system for certain IAS is feasible. Passive acoustic monitoring offers continuous, non-intrusive detection of IAS over large areas. However, its usefulness is limited to sound-producing taxa and complicated by noisy coastal environments, making it a promising yet still experimental complement to other surveillance methods.

2.2 Using eDNA in monitoring and early-warning systems

Recent advances in molecular ecology have positioned eDNA methodologies at the forefront of biodiversity monitoring and IAS management (e.g. Altermatt et al., 2025), and in this section we want to summarize its use in this field. By analyzing genetic material shed into the water (e.g., skin cells, mucus, feces, urine, blood, and gametes), eDNA can reveal the occurrence (or recent presence) of species in the wider area, including elusive or low-density species often missed by traditional surveys (Gilbey et al., 2021; Brys et al., 2021a; Bommerlund et al., 2023; Van Driessche et al., 2024). Several case studies have reported that eDNA detects more NIS and IAS than conventional surveys (Varrella et al., 2025). eDNA approaches enable rapid, non-invasive sampling across many sites, with ongoing advances in qPCR/ddPCR and modelling offering insights into abundance and colonization dynamics (Doi et al., 2019; Everts et al., 2022). However, its application is still limited by methodological challenges such as primer biases, semi-quantitative outputs, DNA degradation and transport effects, and incomplete or inconsistent reference databases, all of which can lead to false positives or negatives (Van Driessche et al., 2022; Van Der Loos and Nijland, 2021; Jarman et al., 2024). While challenges remain, eDNA is increasingly integrated into routine surveillance and automated sampling systems (De Brauwer et al., 2023). Standardization of protocols and validation against conventional taxonomic methods therefore remain essential (Theroux et al., 2025), meaning that eDNA should be viewed not as a replacement but as a complementary approach that, when integrated with traditional surveys, can greatly enhance the scope and effectiveness of marine biodiversity monitoring (Varrella et al., 2025; Xanthopoulou et al., 2025).

These molecular approaches provide a rapid, cost-effective, and highly sensitive alternative to conventional methods that rely on labor-intensive field surveys and morphological identifications (Rees et al., 2014). Because NIS and IAS are often difficult to detect, particularly during the early stages of incursion when populations are sparse, this non-invasive technique is especially well-suited for early detection and rapid response, both of which are critical for preventing widespread ecological and economic damage (Martinez et al., 2020).

One of the principal advantages of eDNA-based monitoring is its exceptional sensitivity. It enables the detection of trace amounts of genetic material shed by organisms, allowing researchers to identify newly introduced IAS, long before they can be reliably observed through traditional survey methods (Flitcroft et al., 2025). Even low concentrations of eDNA can be amplified using molecular techniques such as quantitative PCR (qPCR) or droplet digital PCR (ddPCR), providing managers with an indispensable early-warning capability for rapid response and containment (Fonseca et al., 2023). This enhanced sensitivity is particularly valuable for detecting elusive, small, cryptic, or juvenile life stages of invasive organisms that would otherwise go unnoticed during conventional sampling campaigns (Figure 2).

Equally important is the ability of eDNA to provide spatially explicit information on the distribution of NIS and IAS across extensive and logistically challenging aquatic systems (Jarman et al., 2024) (Figure 2). Standardized sampling protocols can be deployed in remote or inaccessible regions where physical surveys are difficult or prohibitively expensive, ensuring that even low-density populations are detected and accurately mapped (Jerde et al., 2019). The "take once, use many" principle inherent in eDNA sampling further enhances this capacity, as a single water sample can yield information on multiple species simultaneously, facilitating comprehensive assessments of biodiversity and invasive species distributions (Larson et al., 2020).

Furthermore, eDNA techniques can provide insights into population relative abundance by quantifying species-specific DNA concentrations, which have been shown to correlate with biomass and population density (Brys et al., 2021b, 2023; Everts et al., 2022). In this way, eDNA-based monitoring not only confirms species presence but also generates quantitative data that can inform assessments of ecological impact and the potential influence of IAS on native communities (Everts et al., 2024). When integrated with citizen science, these approaches can further increase monitoring throughput, as community-collected samples contribute to large, statistically robust datasets that enhance the resolution and reliability of abundance estimates (Bylemans et al., 2025).

The value of eDNA data is also likely to grow in long-term ecological monitoring and impact assessment studies. By incorporating eDNA time-series data, researchers can track both the arrival of new NIS and IAS (Baki et al., 2025) and their cascading effects on native biodiversity, community resilience, and resource availability (Figure 3). Such integrative assessments are particularly critical in ecosystems experiencing rapid environmental change or high anthropogenic pressure, where even subtle shifts in species composition can have far-reaching consequences for ecosystem functioning and services. These molecular techniques enable researchers and managers to conduct comprehensive, cost-effective impact assessments, ultimately accelerating the development of adaptive and responsive conservation strategies.

2.3 Citizen science in monitoring biodiversity

Citizen science initiatives are important in monitoring marine biodiversity, as they mobilize divers, fishers, and coastal communities to report unusual sightings through social media or other digital platforms. Engaging citizens substantially expands the monitoring capacity across space and time (Edgar and Stuart-Smith, 2014; Giovos et al., 2019). Citizen science offers extensive reach and

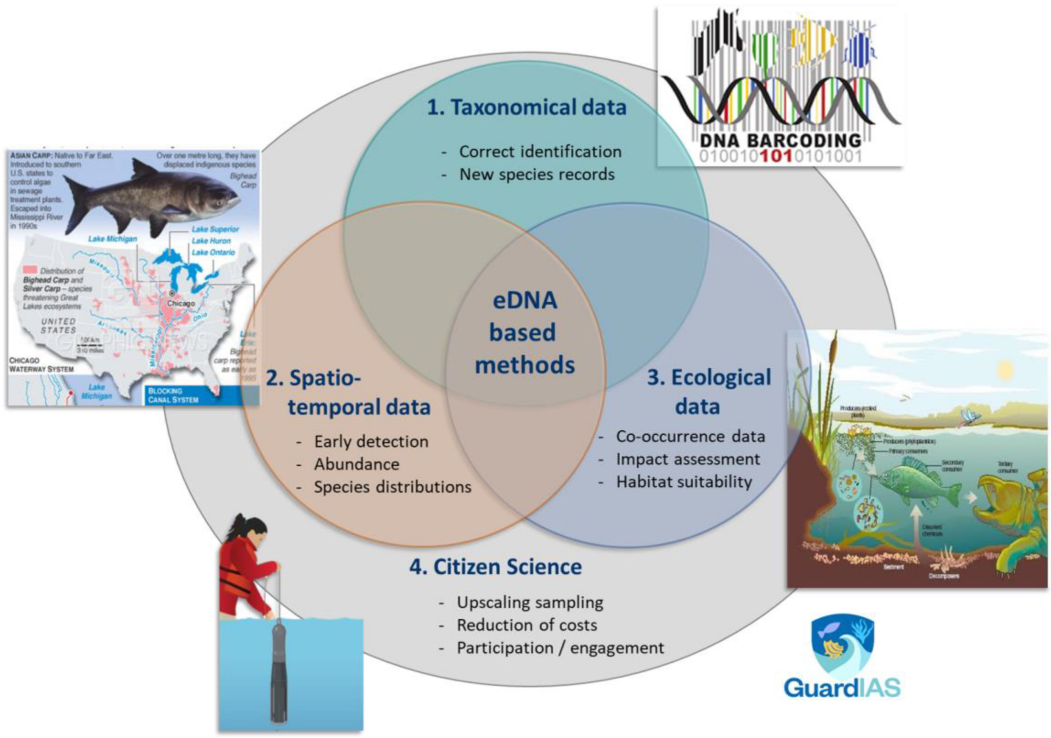

FIGURE 2
Conceptual illustration showing how the integration of eDNA-based monitoring with citizen science enhances large-scale surveillance of invasive alien species (IAS) by providing: (1) taxonomical data for better and faster identification of new species; (2) spatio-temporal data that improve early detection, abundance estimation, and distribution mapping; and (3) ecological data that support assessments of habitat suitability, species co-occurrence, and ecological impacts.

public engagement benefits, as a network of volunteers can monitor many more sites than professionals alone, often at minimal cost (Delaney et al., 2008; Buzinkai et al., 2023). However, observations by untrained participants may suffer from misidentifications or inconsistent effort (which also can occur in expert datasets). Hence, training citizen observers, focusing efforts through simple protocols (e.g., reporting a short list of target IAS), and implementing the verification and curation of citizen data by scientists are important elements of a citizen science project.

The integration of eDNA sampling with citizen science initiatives has the potential to greatly expand data collection efforts (Figure 2). By engaging trained volunteers and local stakeholders, these programs can complement professional monitoring and substantially increase the geographic and temporal scope of

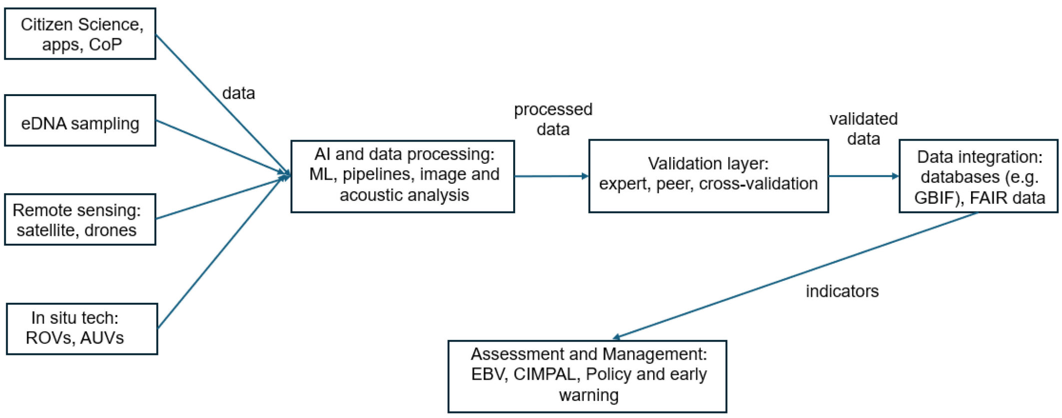

FIGURE 3
Workflow illustrating the integration of topics studied in this research (citizen science observations, remote sensing, e-DNA, *in situ* technologies), further processing of data, validation and data integration, for assessment and management of marine biodiversity, including alien species. CoP: community of practice; ROV, remoted operated vehicle; AUV, Autonomous Underwater Vehicles; AI, artificial intelligence; ML, machine learning; GBIF, Global Biodiversity Information Facility; FAIR, Findable, Accessible, Interoperable, Reusable; EBV, Essential Biodiversity Variables; CIMPAL, Cumulative IMPacts of invasive ALien species.

biodiversity assessments (Larson et al., 2020). Together, these complementary approaches support an adaptive management framework in which rapid detection and real-time information feed directly into timely, data-driven decision-making (Rees et al., 2014; Browett et al., 2020).

Hence, the future of marine NIS and IAS detection lies in integration. Combining traditional approaches with robotic, genetic, acoustic, and citizen-sourced data into centralized systems can generate cross-validated results and feed early warning systems, enhancing the defense against marine biological invasions (Katsanevakis et al., 2024).

2.4 Machine learning in monitoring biodiversity

Machine learning has been used for identification and counting of a wide range of marine organisms, supporting biodiversity monitoring in the ocean (Rubbens et al., 2023; Kühn et al., 2025). Applications range from microorganisms, whose rapid and accurate identification of microbes is difficult, but has been addressed using Raman spectroscopy coupled with one-dimensional convolutional neural networks (Liu et al., 2020). In the case of phytoplankton and zooplankton, machine learning has been used more intensively for identification using digitalization devices, such as digital cameras and scanners (Zarauz et al., 2009; Bachiller et al., 2012; Grandremy et al., 2023). Macroalgae and angiosperms identification has been undertaken with machine learning both from underwater and satellite imagery, with a focus on underwater identification and classification from satellite (Wang and Hu, 2021; Martínez-Movilla et al., 2024). Benthic species have been also extensively studied using underwater videos or photoquadrat images in combination with machine learning (Rubbens et al., 2023). At higher trophic levels, fish, seabirds, reptiles, and marine mammals have also been identified using machine learning, sometimes combined with citizen science approaches (French et al., 2020; Dujon et al., 2021; Edney and Wood, 2021; Lekunberri et al., 2022; Hamard et al., 2024).

Development of trustworthy machine learning based systems requires three pillars: socio-economic and legal viability, data governance, and both technical and scientific robustness (Fernandes-Salvador et al., 2026). The technical process of developing these systems consists of several steps, including data collection, data pre-processing, model training, validation, deployment and interpretation of results.

The first step, data collection, often requires expertise in other areas, such as instrumentation, sampling design and protocols, and often takes advantage of already existing surveys. The whole process does not consist solely of training a model from the collected data. In most cases, real-domain collected datasets are often not directly suitable for model training due to noisy or missing values and outliers; pre-processing effort can significantly improve the final model (Zhang et al., 2003; Uusitalo, 2007; Fernandes et al., 2010).

Therefore, there is a need to estimate the performance of the whole model building a process or pipeline (pre-processing and model) to assess the usefulness, power, and reliability of all the steps instead of only the final model itself (Reunanen, 2003; Statnikov et al., 2005; Fernandes et al., 2015). Furthermore, robust validation schemes, such as repeated k-fold stratified cross-validation or bootstrapping, involve multiple data partitions, which not only provide more reliable error estimates (Rodríguez et al., 2013), but also enable statistical comparisons between methodologies, for example using the corrected paired t-test (Nadeau and Bengio, 2003). However, data bias on training data can lead to underperforming systems if not contrasted with other sources of information (Taconet et al., 2019; Lekunberri et al., 2022). Taconet et al. (2019) compared the machine learning classification of vessel activity with a database of recorded catches to highlight discrepancies between the two data sources. Although neither dataset represents an absolute ground truth, the inconsistencies revealed several limitations in the machine learning based classification. Similarly, Lekunberri et al. (2022) compared on–board automated fish species identification and size measurements using machine learning with manual estimates during port subsampling. Despite neither approach fully classifying and measuring all captured fish, both should produce similar estimates or help identify potential sources of systematic error or bias.

Finally, the suitability of trained models for real-world deployment must also be considered. Operational constraints such as hardware availability, computational requirements, latency, scalability, and maintenance costs can limit the applicability of high-performing models. Hence, these constraints should be considered during model design and selection. Machine learning systems become economically viable largely when they can be scaled, since higher data processing volumes allow fixed development and infrastructure costs to be distributed more efficiently, improving overall cost–effectiveness (Moro-Visconti et al., 2023; Zipperling et al., 2026).

3 Application of emerging technologies to monitor biodiversity at sea

3.1 Machine learning in imaging and species identification (computer vision)

In this context of biodiversity monitoring, the analysis of underwater imagery has evolved substantially over the past two decades, driven by advancements in image resolution, sensor technology, computational power, and image analysis techniques. This progress has led to an exponential growth in the marine imaging data, making traditional manual review approaches increasingly impractical due to their laborious processes and potential annotator's bias (Culverhouse et al., 2003; Durden et al., 2016; Lekunberri et al., 2025). This challenge highlights the need for automated solutions as an alternative, or complement, to manual annotations (Beijbom et al., 2015; Schoening et al., 2016). Within automatic approaches, early methods relied on manually extracting visual features from images, using domain knowledge, and passing them into classical machine learning algorithms to recognize patterns and objects (Schoening et al., 2012; Seiler et al., 2012). In contrast, modern approaches based on deep learning models automatically learn hierarchical features from raw image data, consistently achieving state-of-the-art results. The downside of deep learning is that it requires a vast amount of labelled data to learn the relations between image features and their corresponding labels.

The quality and diversity of datasets are critical determinants of model performance. However, in the marine domain, these datasets suffer from several challenges due to the complexity of marine objects and the underwater environment (Fu et al., 2023). Common obstacles in computer vision, such as obstruction (overlapping organisms, schooling fish), animals in variable orientation and scale, and camouflage, make it difficult to create robust models with species that exhibit high-interclass similarity and low intraclass variance. Furthermore, environmental factors like marine snow, turbidity, color cast in different water bodies, and light variance from wave action in shallower water further degrade image quality and complicate the transferability of models.

This is where data preprocessing plays a key role in addressing these and other challenges, such as class imbalance or domain shift. There are several proposals for image enhancement (Zhang et al., 2019; Anwar and Li, 2020; Raveendran et al., 2021), data augmentation techniques (Kumar et al., 2024; Doig et al., 2025), domain shift adaptation (Csurka, 2017), and for developing shared datasets, such as FathomNet (Katija et al., 2022), CoralNet (Beijbom et al., 2015), DeepFish (Saleh et al., 2020), and BenthicNet (Lowe et al., 2025). These public datasets provide valuable resources for training and benchmarking computer vision models, although compared to other domains such as everyday images (e.g., cars, food, cats), the available images are scarce. In Schoening et al. (2018), a guideline for data acquisition, curation and management is proposed.

Although, several public datasets for underwater imagery are available, they often lack the specific requirements of research projects and pertinent data gathering information (sensor, water conditions) that can contextualize model performance. Limitations may arise due to the absence of target species, varying imaging devices, or environmental conditions. Consequently, a common, although time-consuming approach, is to manually annotate a custom dataset using existing annotation tools that range from domain-specific like BIIGLE (Langenkämper et al., 2017), photoQuad (Trygonis and Sini, 2012), SQUIDLE+ (Proctor et al., 2018) and CoralNet (Beijbom et al., 2015) to general-purpose solutions like Computer Vision Annotated Tool (CVAT.ai Corporation, 2023) and Roboflow (Roboflow, 2019). These tools vary in terms of cost (free, paid, or hybrid licensing models), user interface (e.g., web based), and functionalities (e.g., semi-automated labelling). Choosing the right tool depends on clearly defined project goals and annotation tasks and factors like supported formats (e.g., COCO, YOLO), artificial intelligence-assisted features, collaborative capabilities, quality control mechanisms, and implementation effort should be considered. For further information on annotation tools (see Althaus et al., 2015; Gomes-Pereira et al., 2016; Schoening et al., 2016, and Zurowietz and Nattkemper, 2021).

Effective model training requires careful consideration of architecture, frameworks, evaluation strategies, task requirements and dataset characteristics. Computer vision tasks typically include: i) image classification, which assigns a specific label to the entire image; ii) object detection, which consists of localizing and identifying multiple objects within an image; and iii) image segmentation, which assigns a class label to each pixel, enabling precise object or habitat delineation. Typical models used in underwater problems are Mask R-CNN (He et al., 2017) for instance segmentation, Faster R-CNN (Ren et al., 2016) and YOLO (Jocher et al., 2023) for object detection and tracking, UNet models for habitat segmentation (Zhang et al., 2022), ResNet for classification (Jocher et al., 2023). Newer models based on transformer architectures demonstrate better performance (accuracy) than CNNs in vision AI benchmark datasets but have greater requirements for training (number of samples, hardware) than their CNN counterparts (Dosovitskiy et al., 2021). The decision between base architectures is more nuanced but in data constrained domains like marine imagery, CNNs are a practical first choice. To train the selected model, popular frameworks include PyTorch, Ultralytics (YOLO), Roboflow, TensorFlow, and Keras. It is important to highlight a common model training strategy, especially in computer vision where datasets are scarce, called transfer learning. This approach adapts pre-trained models for a specific task by fine-tuning them on a smaller, task-specific dataset, significantly reducing the need for extensive labelled data and computational resources.

Once the model is trained, the evaluation metrics will depend on the task, where accuracy, precision, recall, and F1-score are commonly used for classification; mean average precision (mAP) for detection; and intersection over union (IoU) for segmentation. Finally, ensuring fair comparison across models needs consistent dataset splits, balanced class distributions, and transparent reporting of hyperparameters and training protocols.

3.2 Active engagement of citizens in marine monitoring

Active engagement of citizens in biodiversity monitoring (including IAS) needs to face several specific challenges. In social perception, major threats to health of aquatic ecosystems are plastic pollution, oil spills, algal blooms, turbidity, odor, and overall aesthetic quality (Flotemersch and Aho, 2021; Froehlich et al., 2024), while the awareness of environmental impacts of biological invasions is often limited (Banha et al., 2022). In fact, the understanding of the IAS term is affected by polysemy and misconceptions, determined by contexts, value and belief systems, as well as social and cultural conditions of individuals (Kapitza et al., 2019; Probert et al., 2022). Practices of IAS control can misalign with citizens' ideas of 'helping nature' (Pagès et al., 2019), resulting in a weak willingness to act. Even recognition of charismatic aquatic species as either alien or native is problematic (e.g. see Clusa et al., 2018; Kochalski et al., 2019, for examples from freshwater habitats; and Martínez-Laiz et al., 2019, for marine habitats).

In this context, while involvement of citizens is repeatedly advocated as a 'vital' approach for the management of IAS (Roy et al., 2018; Price-Jones et al., 2022; Tricarico, 2022; Pocock et al., 2024), the active, long-term engagement of citizens remains a challenge (Pagès et al., 2019). So far, most citizen science projects addressing aquatic IAS in Europe have been focused on collecting species records. Some noteworthy examples include the Jellywatch programme[1], launched by the Mediterranean Science Commission (Boero et al., 2009); the RINSE "That's Invasive!" app[2] and the KORINA app[3] in northwest Europe (Adriaens et al., 2015); the Greek project "Is it Alien to you? Share it!!!"[4] launched by the Environmental NGO iSea (Giovos et al., 2019); the IAS Portal launched by the Finnish Museum of Natural History (Lehtiniemi et al., 2020). Besides providing valuable data and showing high effectiveness for IAS early detection (González-Moreno et al., 2025), these initiatives contribute to increased public knowledge and awareness of biological invasions, potentially resulting in greater support for conservation and management actions (Tricarico, 2022). Yet, according to Haklay et al. (2021) classification of citizen science typologies, these activities fall in the category of passive sensing and occasional reporting, requiring a short-term effort (the time it takes to take a picture and upload it to an app, or social-media group), with a single-stage involvement. Also, these initiatives inevitably attract participants from limited society groups (e.g., professional and recreational fishers, divers, environmentalists).

To engage a wider segment of the population in activities that are not just occasional records but also management practices, new tools and approaches are needed. Motivating larger groups of citizens to become actors in the management of aquatic IAS and overcoming their possible reluctance to endorse IAS control due to emotional attachment to some species (Pagès et al., 2019), requires crossing boundaries of classic science communication. Arts, especially participatory arts, have been shown to create a context able to uniquely stimulate emotions and critique, which are fundamental to inspire behavioral change and willingness to act (e.g. MarinArt challenge, from GES4SEAS project[5]). The integration of different art forms with education on topics such as environmental sustainability, climate change, and nature-based solutions has already been shown to be fruitful (Jacobson et al., 2016; Burke et al., 2018; Conte et al., 2024). In particular, the approaches of social theatre, community theatre and dance, and multi-performative dramaturgy have been shown to develop community capacities (Pasetto and Innocenti-Malini, 2022), which are required to face an extensive complex problem such as biological invasions. Art practices have also the advantage of attracting portions of society that are less interested in environmental or scientific issues, hence giving the opportunity to engage citizens of different ages, social and cultural backgrounds, professions and health conditions.

With these premises, the project GuardIAS (Katsanevakis et al., 2024) has developed the novel concept of BioArtBlitz to engage citizens in the management of aquatic IAS. BioArtBlitz events combine art performances by professional artists and field activities, to involve citizens in an emotional and imaginative way. These events, co-designed by biologists, humanities researchers, and artists, specifically deal with IAS impacts and management strategies, also addressing controversial aspects, such as eradication actions. Following the performances, participants join field activities to test IAS control measures and discuss strategies to improve them, hence overcoming the passive context of normal content consumption and becoming active agents of change. Various formats of BioArtBlitz will be tested during the project GuardIAS, to determine strengths and weaknesses of the different approaches in terms of methodological issues, effectiveness, and evaluation systems. This represents a novel way to engage citizens in science with a creative and emotional basis.

3.3 Species identification through machine learning and Citizen Science: Harnessing iNaturalist potential

Machine learning and citizen science, used together, are powerful tools to extend the reach of traditional biodiversity monitoring (Earp and Liconti, 2020; Ditria et al., 2022). A leading example is iNaturalist[6], a platform that combines citizen science and computer vision to rapidly collect and verify many observations (Mesaglio and Callaghan, 2021). With over 3.8 million users worldwide, iNaturalist has built a successful Community of Practice (CoP) which is key to promoting participation and thus obtaining many records, alongside the continuous development and improvement of Citizen Science platforms and observatories.

iNaturalist has become one of the largest biodiversity-focused social networks, dedicated to sharing species observations across its global community (Munzi et al., 2023). The platform generates records from densely populated lands to remote marine areas, thereby covering a wide range of habitats. By combining computer vision models with a global network of contributors including expert identifiers, iNaturalist is demonstrating how machine learning and citizen science can jointly expand the spatial, temporal, and taxonomic scope of marine biodiversity monitoring far beyond what scientific teams can achieve alone (e.g. Rocha et al., 2024; Wolfe et al., 2025).

Regular automated integration of iNaturalist observations into the Global Biodiversity Information Facility (GBIF) ensures that records meeting "research grade" criteria (valid date, geo-localization and photographic or acoustic media with agreement by at least two-thirds of the identifiers), are rapidly available and interoperable. This makes iNaturalist observations valuable, verifiable resources for research and biodiversity monitoring (Ackland et al., 2024). Since 2017, iNaturalist has integrated a computer vision model based on deep convolutional neural network (DCNN) to provide rapid species suggestions (Reeb et al., 2022). This model is continuously improving as research grade observations continue to enrich the training dataset, alongside additional model refinements, such as geo-model integration further enhancing prediction accuracy. A major advance came with the release of the computer vision

1 https://www.ciesm.org/marine/programs/jellywatch.htm.
2 https://www.gbif.org/tool/82123/thats-invasive-app-by-rinse.
3 https://www.gbif.org/tool/82125/korina-smartphone-app.
4 https://isea.com.gr/activities/citizen-science/is-it-alien-to-you-share-it/?lang=en.
5 https://www.ges4seas.eu/marinart-challenge-urban-art-for-europes-seas/.
6 https://www.inaturalist.org.
7 https://www.inaturalist.org/posts/75633-a-new-computer-vision-model-v2-1-including-1-770-new-taxa.

v2.0 model in August 2022, trained on 60,000 taxa and 30 million photos. Earlier versions were trained from scratch (i.e., without pre-trained weights or transfer learning), requiring full model retraining for each update. This reportedly took on the order of 4–9 months given the size of the dataset and computational demands[7]. The v2.0 model introduced transfer learning, enabling faster integration of new taxa and more frequent computer vision model retraining. Since then, the model has been re-evaluated every one to two months, with the most recent version (v2.31, released May 2026) covering 118,700 taxa (an increase of 1,382 taxa since v2.30 in April 2026). While image-based identifications remain the most robust, the platform has also begun to incorporate sound recordings, creating new opportunities for monitoring taxa that are acoustically recognizable. Together, these developments highlight iNaturalist's potential to provide scalable, participatory biodiversity monitoring wherever targeted taxa are identifiable from images or sounds (Roberts et al., 2022; Garretson et al., 2023). Dedicated projects have even demonstrated the platform's ability to document rare taxa in their natural habitats. For example, the "First Known Photographs of Living Specimens" initiative recorded 406 observations of rare butterflies, including the only known record of *Splendeuptychia argyropsacas* Bryk, 1953, other than its 1953 type specimen (Mesaglio et al., 2021).

Despite its many strengths, the iNaturalist approach is not universally applicable across all taxa or habitats. Species that are cryptic, microscopic, or inhabit hard-to-access environments, such as the deep sea, are poorly represented, as they cannot be reliably identified from photographs or casual observations (Rocha et al., 2024). In addition, the opportunistic and unstructured nature of citizen science sampling can introduce spatial biases (Geurts et al., 2023). Observations are typically concentrated in easily accessible and frequently visited areas, such as urban coastlines, while remote islands or offshore habitats remain under-represented. This uneven distribution can distort our understanding of biodiversity patterns if the data are not carefully interpreted (Di Cecco et al., 2021). Furthermore, although the integration of machine learning-based species suggestions and community validation greatly reduces error rates, the risk of misidentification remains, particularly for taxa that require expert-level knowledge to distinguish (e.g., Munzi et al., 2023). To maximize reliability, robust data curation protocols are essential (Ackland et al., 2024), and citizen science data should ideally be combined with systematic, structured surveys conducted by scientific teams (Roberts et al., 2022). To minimize species misidentification in iNaturalist observations, taxonomists and scientists have a key role to play by actively curating identifications and sharing expertise with the engaged, learning-oriented iNaturalist community. This collaborative approach further enhances citizen scientist engagement, improves computer vision model accuracy, increases the proportion of observations reaching research grade and being integrated to GBIF, while improving dataset quality and scientific value (Rocha et al., 2024).

Overall, machine learning-assisted citizen science can transform marine biodiversity and invasive species monitoring. However, realizing this potential requires active expert involvement, rigorous data curation and engagement with the citizen community to build skills and ecological literacy. While large observer networks generate vast datasets, their true value depends on careful methodological curation, complemented by structured traditional scientific surveys.

3.4 Another example of participatory initiatives to reduce the marine biodiversity gap of knowledge

When considering large scale monitoring citizen science programs, establishing (and consolidating) regional CoP is key for promoting participation and thus obtaining many records, alongside the continuous development and improvement of Citizen science observatories.

In this context, MINKA[8] is a participatory observatory, inspired by iNaturalist, a reference platform with a worldwide community. MINKA has expanded the observational capabilities allowing participants to contribute not only to biodiversity observations but also with environmental observations (such as marine litter) at their own pace. The user interface has been adapted as well to facilitate marine oriented communities, since iNaturalist is biased to terrestrial projects (for example, the major marine taxa are grouped as "other organisms" in the iconic representations, making it more difficult to select specific marine taxa in any search query). Biodiversity observations are validated collaboratively by other users and further reviewed by data curators of the platform with marine expertise background, before being integrated into global data repositories as GBIF. The observatory, in continuous development, counts on end users' feedback to codesign and implement new features for both the platform and the app. AMOVALIH, a novel tool developed in MINKA within ANERIS project, is a hybrid intelligence system which supports bioimage analysis, by combining automated classification with human expertise (Fornós et al., 2023). The system operates through an interactive workflow in which users upload an observation image and can request machine learning support. The user can select a model or let the platform select the most suitable model from a registry of available classifiers and generates the top candidate species identifications. These suggestions are subsequently validated by the users who can confirm the proposed identification, provide alternative species names, or refine the classification through discussion. This iterative process ensures that automated predictions are systematically reviewed and improved by human input. The architecture is designed to be extensible, enabling the integration of external APIs (e.g., Pl@ntNet[9], Imagga[10]) and custom hierarchical artificial intelligence models to expand taxonomic coverage (Fornós et al., 2023).

As a proof of concept, the CoP for marine observations has been developed in the Catalan coast (NE of Spain) following two main strategies for engagement: first, MINKA uses the conceptual Janus framework, proposed by Liñán et al. (2022), in which volunteer participants not only interact with academics, but also with enablers whose role is mobilizing participants and providing resources to facilitate their participation (for instance, snorkeling/diving gear or

8 https://minka-sdg.org/.
9 https://plantnet.org/en/.
10 https://imagga.com/.

underwater cameras) and with facilitators, usually local governmental institutions that provide facilities for organizing activities in dedicated meetings (such as dissemination gatherings). The second strategy is the design of specific participatory events, BioMARathons, which are extended BioBlitz taking place during large periods, usually from the first weekend of May until mid-October (Liñán Moyano et al., 2026). These events have been implemented to enhance volunteer participation in marine biodiversity monitoring since 2021 in the Catalan coast, obtaining a retention rate of participants after each edition who keep on contributing all year around.

The CoP has consolidated in the Catalan coast, reaching outstanding numbers over the past five BioMARató editions: surpassing 94,000 observations in 2025, registering over 2,000 species by more than 500 volunteer participants, obtaining marine biodiversity observations in the whole Catalan coastline (Salvador et al., 2025). This model was replicated in the northern Portuguese coast, starting in 2023 with a few pilot activities, and deployed in 2024 as “BioMARatona Norte”, obtaining interesting results in Atlantic intertidal communities (Monteiro et al., 2025).

The large number of recorded observations by the two CoPs (Companys et al., 2025a) have contributed to increase the marine biodiversity knowledge of Catalonia and Northern Portuguese coast. These recordings are important as they helped obtaining over 30 first records registered on the Catalan coast (e.g. Salvador et al., in prep), monitoring of NIS and IAS, as for instance the macroalgae *Asparagopsis taxiformis* (in Catalonia, unpublished) or *Undaria pinnatifida* (in Portugal, Humet et al., 2025), alongside with threatened and sensitive species (Companys et al., 2025b).

Establishing local CoPs, involving community enablers to enhance the participation, is key to developing and consolidating local networks. In this context, it is important to provide feedback to the participants and to disseminate the results and discoveries made thanks to their contributions, while always acknowledging their participation. At the same time, valuing end-users' feedback during the continuous development of the observatory and the implementation of AI-assisted classification with human validation will increase quality control.

3.5 Data-validation solutions for citizen science data on IAS using smartphones

As shown in Sections 3.2-3.4, citizen science is growing in popularity in the field of invasion biology, even if it is still challenging in aquatic environments and biased towards certain taxa, e.g. plants and insects (Encarnação et al., 2021). Many IAS projects use smartphone apps to report the presence of a new species or update species distribution (Teacher et al., 2013; Price-Jones et al., 2022). As smartphones and GIS technologies are part of our daily life, citizen science apps make geoparticipation easier than ever before (Hognogi et al., 2023). There are many advantages in using apps, such as raising awareness of stakeholders (e.g. anglers, gardeners, beekeepers, hunters, farmers, environmentalists), reducing the cost of monitoring and improving science and technology literacy among participants (Crall et al., 2015). Data validation involves standardized, often automated checks on the completeness, accuracy of transmission and validity of the content of a record (James, 2006). Data can be validated in different ways: peer verification, expert verification, automatic quality assessment and model-based quality assessment (Balázs et al., 2021). These approaches are not mutually exclusive and validation takes place before, during and after an observation to reduce problems and errors. Model based quality assessments, for their complexity, are often performed during the analysis phase of the data, while expert and peer verifications are the most common approaches (Balázs et al., 2021). Indeed, most citizen science projects on IAS have a validation step and during a survey on 103 IAS citizen science projects conducted in Europe, 91 projects indicated the use of validation procedures (Price-Jones et al., 2022), mainly based on expert validation, alone or with peer validation and automatic systems.

Problems in validation exist if, e.g. the picture is not good enough and/or does not report the traits allowing the identification; even if the necessary traits are present, identification and validation could be sometimes difficult or even impossible in case of very similar species. These shortcomings are troublesome when validation is needed for promoting management actions of regulated IAS, particularly for early detection and prompt eradication. To overcome these flaws, distinctive species with low probability of misidentification should be the target of an observation, while a preliminary training phase for citizens could be planned before starting a project (Pocock et al., 2024), and spatio-temporal criteria, such as the currently known/possible range and seasonal range, should be included in the app to help the identification, and subsequently the validation. For problematic species, genetic analysis and/or traditional monitoring approaches can be conducted to complement citizen science activities. Moreover, strengthening the peer validation aspect empowers the users in contributing to quality control and favors additional engagement (Adriaens et al., 2015). Finally, to avoid delay in notifying detections of new introduced species, a prioritization approach in validating records should be considered, especially when the number of submitted observations is high (e.g. in the Norwegian Species Observations Service system observations of red-listed and IAS species are prioritized).

When the validation process is fully implemented, citizen science can be very powerful in reporting first records of new IAS, even before the official systems (González-Moreno et al., 2025). Besides this, citizen science through apps has also the currently underexplored potential to report species interactions and IAS management outputs (Groom et al., 2021; Pocock et al., 2024) and could provide a great contribution to better understand (and map) the impacts of IAS and the success of control activities.

4 Using biodiversity data in interpreting and assessing impacts

4.1 Using essential biodiversity variables

As shown in Sections 2 and 3, the advancement of sensing devices and machine learning algorithms is increasing the speed of data collection and analysis. To support evidence-based decision making in biodiversity conservation, suitable frameworks are necessary for interpreting and synthesizing this newly generated data. Two conceptual frameworks of biodiversity have emerged in recent years, encompassing the different contexts and scales, the Essential Biodiversity Variables (EBV) and the Essential Ocean Variables (EOV) concepts (Pereira et al., 2013, 2024; Miloslavich et al., 2018; Muller-Karger et al., 2018b).

The EBV framework was established by the Group on Earth Observation of Biodiversity Networks (GEO-BON) to facilitate the systematic collection, sharing, and utilization of biodiversity data. EBVs provide a structure that delineates the variables measured (Pereira et al., 2013; Jetz et al., 2019) and from which indicators can be derived. The framework is based on the idea that EBVs consist of a selected group of variables that collectively represent biodiversity change across multiple biological organization levels and spatial scales relevant to scientific research and management applications (Schmeller et al., 2017; Jetz et al., 2019). GEO-BON identified 22 candidate EBVs categorized into six organizational levels: "genetic composition", "species populations", "species traits", "community composition", "ecosystem structure", and "ecosystem function". These categories are intended to be broadly applicable across different ecosystems (Pereira et al., 2013; Lumbierres et al., 2024). The framework allows for testing hypotheses regarding the drivers of biodiversity change at several biological organization levels.

In turn, EOVs have been promoted by the Integrated Framework for Sustained Ocean Observing (FOO; Lindstrom et al., 2012), which identified the necessity of determining key variables for establishing an integrated global ocean observing system. Building on the precedent set by Essential Climate Variables (ECVs) in climate science, FOO proposed organizing ocean monitoring activities around EOVs, as defined by expert panels. Biology EOVs were proposed by the Biology and Ecosystems (BioEco) panel, created by the IOC-UNESCO Global Ocean Observing System (GOOS) in 2015. Biology EOVs are selected based on criteria such as feasibility and societal relevance, allowing for their consistent application across both developed and less developed regions. This approach enables a standard set of observing variables to be used in a global ocean monitoring system for marine biodiversity (Miloslavich et al., 2018; Muller-Karger et al., 2018b). Biology EOVs are grouped by diversity and biomass, distribution and abundance, and cover and composition. The first two relate to functional groups; the last targets habitat state variables and foundation species like corals, macroalgae, and seagrasses. Implementing each EOV involves specific measurements listed in BioEco Panel Specification Sheets[11], along with ancillary sub-variables for full characterization. For instance, Macroalgal Canopy Cover and Composition includes sub-variables such as canopy percent cover, macroalgal stipe density, canopy species diversity and areal extent.

The EBV and EOV frameworks will provide an increasingly important role in harmonizing biodiversity data. However, the reliability of biodiversity assessments remains contingent upon the quality of the observing programs from which the data originate. Unlike many physical variables that can be sensed globally from satellites (e.g., sea surface temperature), most biodiversity measurements still rely on observations generated from discrete sampling units. Establishing clear hypotheses is key for informing decisions on the spatial and temporal allocation of sampling units, thereby ensuring logically interpretable outcomes from downstream analyses. Here, the term "hypothesis" refers to an expectation or prediction about how species or assemblages would respond to changing environments, including anthropogenic and natural disturbances. While numerous sampling programs are designed to evaluate human impacts at regional scales, international conservation objectives require global syntheses derived from aggregated datasets. Hypothesis-driven monitoring designs addressing specific research questions at regional scales would provide fit-for-purpose data to effectively track the status and trends of biodiversity at larger scales. For example, stratifying sampling units across replicated sites exposed to different levels of anthropogenic disturbance would allow meaningful comparisons to assess regional impacts, but would also offer great flexibility to assess global trends. Depending on the purpose of the global analysis, researchers may opt to utilize only a subset of the data from reference sites to focus on climate-driven trends, while minimizing the influence of local-scale disturbances. Alternatively, one may use the full dataset to evaluate the interactions between global and local-scale processes.

A question-driven sampling design does not need to be complex and even straightforward contrasts between disturbed and reference sites can strengthen causal inference compared to unstructured sampling. Although genuinely pristine sites are rare, we strongly encourage the use of protected areas as reference sites whenever possible. This approach enhances analytical flexibility, helps disentangling the influence of multiple drivers of biodiversity, and improves our ability to assess progress towards global conservation targets (Benedetti-Cecchi et al., 2024).

4.2 Using data to assess NIS and IAS impacts

Katsanevakis et al. (2016) developed CIMPAL (Cumulative IMPacts of invasive ALien species), a spatially explicit index for quantifying and mapping the impacts of multiple IAS on marine habitats, with the flexibility to incorporate different data sources and assessment protocols. This approach, inspired by earlier cumulative human impact assessments (Halpern et al., 2008), calculates an index score per spatial unit by combining NIS and IAS distributions, habitat extent, and impact weights that reflect both the magnitude of ecological damage and the strength of the supporting evidence. Through CIMPAL, hotspots of cumulative impacts can be identified, and NIS can be ranked based on their relative impacts. Since its development, CIMPAL has been applied beyond its original Mediterranean case study and has been considered in international policy frameworks, such as HELCOM and UNEP-MAP Regional Seas Conventions, the EU Marine Strategy Framework Directive, and the European Environmental Agency, with applications in terrestrial, freshwater, and marine environments (Korpinen et al., 2019; Magliozzi et al., 2020; Bartolo et al., 2021; Polce et al., 2023).

11 https://goosocean.org/document-list/168.

The original CIMPAL methodology has since evolved into a family of indices that expand its scope to capture additional ecological and socio-ecological dimensions, as shown in recent publications (Chiappi et al., 2025; Katsanevakis et al., 2025; Zampardi et al., 2026). One such development is CIMPAL-JH, designed to expand CIMPAL to (1) assess the cumulative impacts of IAS, Harmful Algal Blooms (HABs), and jellyfish blooms, and (2) account for interspecific interactions by introducing an additional term accounting for synergistic or antagonistic effects between invasive species (Chiappi et al., 2025). CIMPAL-JH also adapts the species population term to reflect bloom frequency and duration, acknowledging that some pressures are intermittent rather than continuous. Applications of CIMPAL-JH in the Aegean Sea (Chiappi et al., 2025), the Adriatic Sea (Zampardi et al., 2026) and pan-European analyses (Katsanevakis et al., 2025) indicated that while IAS remain the dominant drivers of cumulative impacts, jellyfish and HABs can be locally important, especially in enclosed coastal areas. By integrating multiple biological stressors and their interactions, CIMPAL-JH aligns closely with the ecosystem-based management paradigm and is scalable for global use wherever adequate data exists.

Another significant recent extension is CIMPAL+ (Katsanevakis et al., 2025), which assesses the positive impacts of NIS on biodiversity, such as habitat creation or food provision to native species (Tsirintanis et al., 2022; Vimercati et al., 2022). Using a similar structure to the original index, CIMPAL+ applies impact weights to beneficial rather than harmful ecological outcomes. It is important to note that such assessments of positive effects are not intended to offset negative impacts but to provide a new picture of the ecological roles of NIS and IAS. This refinement introduces a more balanced perspective into invasion biology, highlighting both threats and opportunities, and can inform management decisions that must weigh trade-offs in complex ecological contexts.

The CIMPAL framework has also been expanded further to incorporate ecosystem services (Katsanevakis et al., 2025). The CIMPAL-ES index evaluates how invasions and related pressures affect the delivery of services such as food provision, coastal protection, and recreation. By adding a service dimension to the impact weights, the method distinguishes between negative and positive impacts on human benefits, producing separate CIMPAL-ES– and CIMPAL-ES+ scores. Some species exert both positive and negative impacts, highlighting the complexity of ecosystem service trade-offs. CIMPAL-ES therefore bridges ecological and socio-economic perspectives, making the framework more directly relevant for policy and management.

Together, the CIMPAL family offers a modular and globally relevant toolkit for assessing the cumulative impacts of IAS and related pressures. Each variant builds on the same additive structure but adapts it to address additional ecological questions and challenges. The extensions of the CIMPAL framework reflect the growing demand for holistic, evidence-based assessments that can inform ecosystem-based management, prioritization of management actions, and international policy targets such as the EU Biodiversity Strategy 2030 and the Convention on Biological Diversity's Global Biodiversity Framework (Borja et al., 2024b). The availability of open-source implementation, coupled with automated workflows and cloud-computing support for large-scale applications, further enhances the global utility of the framework.

5 Conclusions

The methods, tools and approaches presented here (machine learning-supported models, citizen science online platforms, eDNA, automated workflows for complex environmental assessments such as the CIMPAL indices, etc.) can change the way marine biodiversity and IAS are monitored and assessed for management purposes (Figure 3). In the past, analyzing quadrat photos from benthic communities needed numerous researchers and was both time- and resource-consuming. Now, these analyses are increasingly conducted with greater efficiency (automated *vs.* manual analysis), allowing for expanded monitoring scales. This improves cost-efficiency, enabling the reallocation of resources toward key tasks such as data interpretation and the translation of results into management and policy measures. This can be further accelerated by integrating multiple complementary techniques within transdisciplinary frameworks (van der Plas et al., 2025).

Artificial intelligence is increasingly incorporated into digital tools for scientific research, such as the Frontiers FAIR^2 platform[12], which extracts metadata from datasets to publish them in open source, following the FAIR principles (Borja et al., 2025). These tools assist researchers in editing and structuring documents, refining, and simplifying the texts, improving the overall readability, and, thus, decreasing the barriers in access for non-English speakers and broad audiences to the scientific results, increasing equity fairness (Makris and Abou-Ismail, 2024).

In monitoring, computer vision models, supported by robust labelling tools and high-quality datasets, offer powerful capabilities for biodiversity monitoring. These approaches enable the automated detection and quantification of organisms and habitats from large volume of underwater imagery. Hence, improving the spatial and temporal scalability of biodiversity assessment compared with time-consuming manual approaches. As marine ecosystems face increasing anthropogenic pressures, the adoption of computer vision approaches is proving instrumental in scaling biodiversity assessments and informing conservation strategies. However, the effectiveness of these models is closely tied to the availability of large, diverse, and well-annotated datasets. Since machine learning performance generally improves with more and better data, continued efforts in dataset creation, standardization, and sharing are essential. These efforts not only enhance model generalizability and reproducibility but also foster cross-disciplinary innovation and accelerate progress in marine ecological research.

In the discussions with the Early-Career Researchers (ECRs), attending the summer school, they expressed ambivalent feelings toward these methods (namely, the use of artificial intelligence), seeing them sometimes as a threat and other times as an opportunity or even a challenge. ECRs are worried by the errors AI models

12 https://www.frontiersin.org/about/fair-data-management.

can produce, but at the same time acknowledge their utility in integrating interdisciplinarity, especially between natural and social sciences, helping overcome certain barriers (e.g. in language, terminologies, coding, etc.). However, relying on artificial intelligence for everything makes ECRs very vulnerable and dependent on external factors, as they acknowledge, recognizing the need to use it critically and protecting scientific integrity (Blau et al., 2024). These concerns from ECRs alert us about the need to include these issues more formally into PhD/ECR mentoring programs and supervision. These programs must consider also ethical issues on the artificial intelligence use in general, and in biodiversity research in particular, keeping a critical and judicious eye (Berger-Tal et al., 2024), and including standardized protocols and guidelines for the future use of these methods in routine monitoring and assessment, with a responsive use (European Commission, 2025). In any case, the ECRs comments from this summer school could be considered anecdotal, and we do not wish to overstate what are essentially informal impressions, despite their interest.

As a concluding remark, it was discussed whether these emerging monitoring and assessment methods are as reliable as traditional ones. However, it was concluded that (i) some methods can produce false results or fraudulent artefacts and datasets; (ii) citizen science can be biased towards certain species; and (iii) eDNA can yield false positives and lacks comparability with traditional methods, posing a challenge for managers. Most attendees recognize that these are additional tools, complementary to those currently in use, but that they will likely not replace them entirely. Even if traditional methods are eventually phased out, expert skills could be redirected towards new applications of those methods. This could open opportunities to examine data from different perspectives, formulate new questions, and rethink processes and phenomena.

Author contributions

AB: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Writing – original draft, Writing – review & editing. MA: Conceptualization, Formal analysis, Resources, Validation, Writing – original draft, Writing – review & editing. LB-C: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Writing – original draft, Writing – review & editing. RB: Conceptualization, Methodology, Project administration, Writing – original draft, Writing – review & editing. BC: Conceptualization, Formal analysis, Funding acquisition, Resources, Visualization, Writing – original draft, Writing – review & editing. AE: Formal analysis, Visualization, Writing – original draft, Writing – review & editing. JF-S: Conceptualization, Formal analysis, Methodology, Resources, Writing – original draft, Writing – review & editing. IG: Conceptualization, Formal analysis, Investigation, Methodology, Resources, Writing – original draft, Writing – review & editing. SK: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Writing – original draft, Writing – review & editing. AM: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Resources, Writing – original draft, Writing – review & editing. JP: Conceptualization, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. LR-D: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing. HT: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing. ET: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Resources, Writing – original draft, Writing – review & editing.

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