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OPEN SCIENCE AND ARTIFICIAL INTELLIGENCE SUPPORTING BLUE GROWTH

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Abstract

The long-term EU strategy to support the sustainable growth of the marine and maritime sectors (*Blue Growth*) involves economic and ecological topics that call for new computer science systems to produce new knowledge after processing large amounts of data (Big Data), collected both at academic and industrial levels. Today, Artificial Intelligence (AI) can satisfy the Blue Growth strategy requirements by managing Big Data, but requires effective multi-disciplinary interaction between scientists. In this context, new Science paradigms, like Open Science, are born to promote the creation of computational systems to process Big Data while supporting collaborative experimentation, multi-disciplinarity, and the re-use, repetition, and reproduction of experiments and results. AI can use Open Science systems by making domain and data experts cooperate both between them and with AI modellers. In this paper, we present examples of combined AI and Open Science-oriented applications in marine science. We explain the direct benefits these bring to the Blue Growth strategy and the indirect advantages deriving from their re-use in other applications than their originally intended ones.

Keywords: artificial intelligence, big data, blue growth, marine science

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1. Introduction

Blue Growth is the long-term European strategy for the sustainable *growth* of the marine and maritime sectors. These sectors currently involve more than 5 million jobs with a gross added value of around 500 billion euros per year (EU Commission, 2019), and thus are integral parts of countries' economy. Blue Growth involves problems that include Big Data and requires Artificial Intelligence modelling (Steven et al., 2019). Extracting knowledge from these Big Data is essential to prevent severe consequences on sea resources alteration due to overfishing, climate change, invasive species, and other disasters.

Generally, the availability of Big Data in most fields of Science is strongly influencing the progress and evolution of Information Technology and consequently, the way Science is approached (Hey et al., 2009). Web and mobile applications and scientific and industrial experiments continuously produce Big Data and demand for new systems to process them, and extract information to produce new knowledge. Issues with Big Data, involve at least the following six "*V*" features: large *Volume*, high production *Velocity*, *Variability* of complexity, *Variety* of representational formats, untrustworthiness (*Veracity*) of the contained information, and high commercial or scientific *Value* of the extracted information. Managing and processing Big Data requires using non-conventional computer science architectures and models (Manyika et al., 2011). Indeed, in the last decade, new Science paradigms have been introduced to manage Big Data while supporting collaborative experimentation, multi-disciplinarity, and the open publication of scientific findings. These paradigms include Open Science, e-Science, and Science 2.0, which are rapidly converging towards the same objectives, i.e. (i) the open publication of results, findings and documents, (ii) the extraction of knowledge from Big Data through proper computational platforms and models, (iii) the implementation of collaborative approaches for services and users to solve complex scientific problems, and (iv) the application of the three *R*s of the scientific method: *R*eproducibility, *R*epeatability, and *R*e-usability of models and results (Andronico et al., 2011; EU Commission, 2016; Waldrop, 2008). In this paper, we will refer to Open Science (OS) as a representative of all the mentioned paradigms.

While new Science paradigms evolve, Artificial Intelligence (AI) is overcoming its traditional boundaries - of research on systems that simulate human intelligence - to meet industrial applications (Jeschke et al., 2017; Leitao et al., 2016). However, AI models often need domain/data experts to collaborate with machine learning experts to refine models and gain high performance. Indeed, a key to achieving high performance in AI modelling is that multi-disciplinary teams cooperate efficiently. In this view, Open Science-compliant systems are crucial to support AI modelling.

In this paper, we present examples of Open Science-oriented computer systems and AI approaches that have addressed and supported the Blue Growth strategy in several ways (summarised in Figs. 1-2). We also present how these systems, initially conceived for marine-science, have generated knowledge and methodologies that other scientists have re-used in other domains, thus extending their range of application. The paper is organised as follows: Section 2 describes standard features of Open Science-compliant platforms; Section 3 reports AI experiments - reported per application topic – supporting Blue Growth and Open Science; Section 4 draws the conclusions.

2. Open Science-oriented platforms

Processing Big Data requires distributed or parallel computing systems that execute computations on several processors/cores or machines in a computer network (Attiya and Welch, 2004). Today, most of the available computing systems do not meet Open Science requirements, because (i) they usually manage specific community requirements, (ii) are much tied to specific repositories and data formats, and (iii) do not support collaborative experimentation. Further, they seldom take into account the open publication of the results and the support of the three *R*s of the scientific method. However, examples of Open Science-oriented platforms are available, that have been developed in the context of marine science and have been extended to other domains (Candela et al., 2016; Coro et al., 2017; Hunter et al., 2012). These platforms include distributed computing systems that are economically sustainable and support flexible and quick import of community-provided processes.

They foster Open Science by embedding their computational platforms within an e-Infrastructure (e-I), i.e. a network of hardware and software resources (e.g. Web services, machines, processors, databases etc.) allowing users residing at remote sites to collaborate and exchange information in a context of data-intensive Science (Andronico et al., 2011; Assante et al., 2019a). An e-I can make a distributed/parallel processing platform (e.g. a High-Performance Computing, a Cloud/Grid Computing system etc.) interoperate with a distributed storage system and other services to manipulate, publish, harmonise, visualise, and access data.

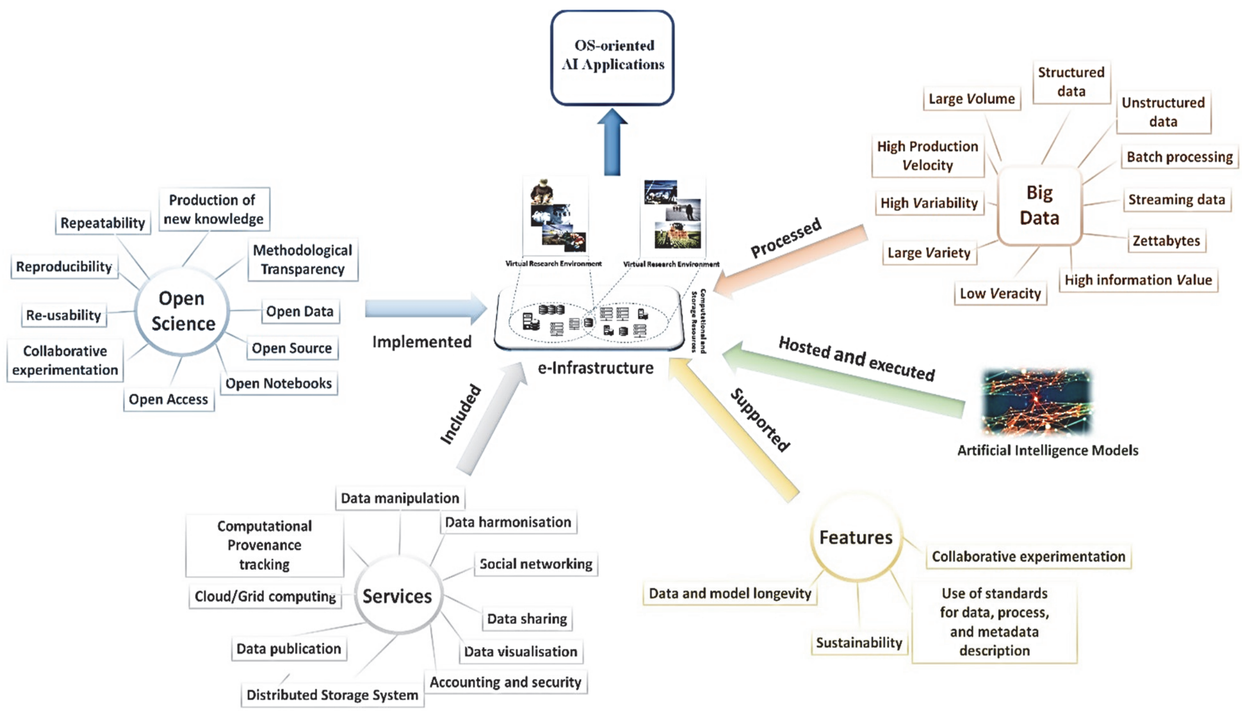

Fig. 1. Logic schema of e-Infrastructure features that support Open Science-oriented AI modelling and Big Data processing

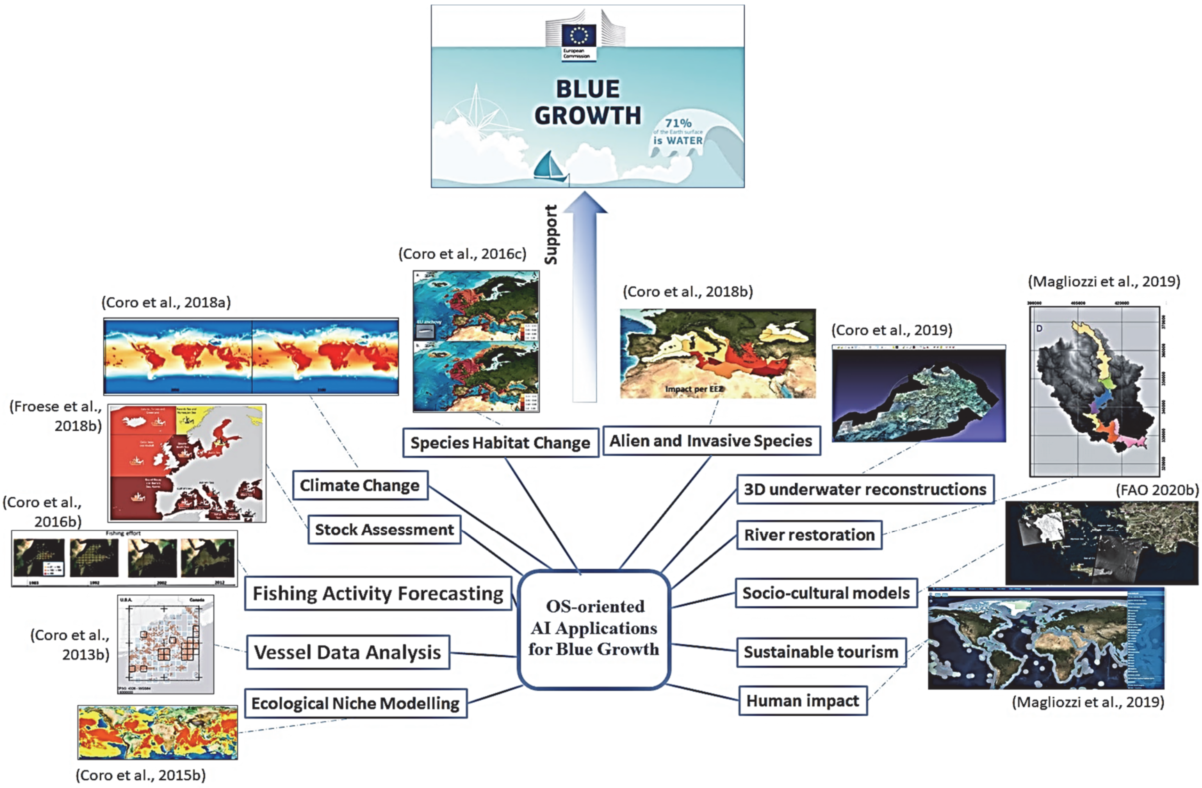

Fig. 2. Logic schema of the support to Blue Growth by Open Science-oriented AI applications

Also, an e-I can manage various access policies and formats for data payloads, data catalogues, security and accounting services, data sharing services, and social networking services.

The distributed computing systems used by e-Is mostly work in the same way as standard computing systems, but they also embed Open Science features. These features allow publishing processes (e.g. scripts, compiled programs etc.) as services that are invocable via a communication standard, and allow for their programmatic exploitation by other services, software, and workflows either provided by the e-I or by the communities using the e-I. Additional services enable quick integration of processes implemented under several programming languages to facilitate their usage and sharing. Usually, an e-I computational platform is also able to interoperate with other services of the e-I while tracking the *provenance* of an executed computation, i.e. the set of input/output data, parameters, and metadata that allow to precisely repeat the experiment. Finally, the platform should also support data and computational result sharing between users through collaborative online spaces.

There are many examples of Open Science-oriented platforms (Kramer and Bosman, 2016). However, few of them manage many of the mentioned properties with the same weight, e.g. D4Science (Assante et al., 2019b) and HubZero (McLennan and Kennell, 2010). Open-access platforms like Zenodo.org, Dataverse.org, and DataDryad.org, focus on the publication and re-use of documents, data, and software. Other platforms, e.g. Jupyter, focus on the reproducibility of processes and workflows (Kluyver et al., 2016), or foster the transparency of scientific workflows and collaborative multi-disciplinary experimentation (Staines, 2018; Thelwall and Kousha, 2015). Overall, a fragmented scenario exists across e-Infrastructures. Usually, scholars must use several platforms to reconstruct and repeat one experiment and retrieve results, documentation, and publications. The main reason is the high cost to manage all requirements of Open Science within one platform. Attempts to inter-connect several e-Infrastructures exist (Assante et al., 2019b; De Roure et al., 2008; Liew et al., 2016) that promote the introduction of standards for workflows' definition and re-use, and for service interactions and data exchange. However, these attempts have achieved minimal success so far.

Indeed, integral to Open Science compliance is the use of communication standards for all services and data that are integrated with the e-I. For example, the Web Processing Service standard (WPS) is commonly used to publish processes as-a-service and to enhance their interoperability with other services (Schut and Whiteside, 2007). The computational provenance can be described through the Prov-O XML-based standard (Lebo et al., 2013). The OAI-PMH standard (Lagoze and Van de Sompel, 2001) is commonly used to describe metadata. The standards defined by the Open Geospatial Consortium (OGC, 2019) are used for geospatial data description and access, and the Statistical Data and Metadata eXchange standard (SDMX, 2004) is used for time series search, retrieval, and inspection. The economic sustainability of Open Science platforms is usually managed by setting up fully automatic service deployment systems and by relying on multiple machine providers (Assante et al., 2016; Coro et al., 2015a).

One of the main advantages for marine scientists when using these platforms is the possibility to execute their processes much faster without developing specific code for the e-I computational platform. This goal is crucial also to run scientific experiments that would be computationally impractical otherwise (Coro et al., 2015b; Froese et al., 2014). Another advantage is the possibility to work collaboratively in a multi-disciplinary team made up of scientists residing very far from each other and having complementary competences. To this aim, Open Science e-Is usually offer virtual laboratories that provide collaboration tools and computational resources dedicated to a research focus group (Assante et al., 2016). For example, within a virtual laboratory, marine biologists can work together with AI experts and exchange data and experimental parameters, while mutually revising experiments and including biologically-oriented knowledge into AI models (Santana et al., 2006; Stockwell et al., 2006). In the next sections, we will show examples of experiments supporting Blue Growth, where multi-disciplinary teams have shared their competences through e-Is to build novel solutions.

Although the will to contribute to Open Science should naturally spur scientists to spend the effort required to share pre-processed data under recognised standards and to update these data continuously, the reality is that Open Science is still not practised spontaneously. This scenario is an open issue for OS-oriented e-Is. Some e-Is have introduced tools to help and accelerate e-I users to (i) standardise data, (ii) automatically import data from heterogeneous repositories, and (iii) make models available as standardised services (Assante et al., 2019a; Candela et al., 2015; Coro et al., 2018c). Other e-Is have proposed academic index calculation promoting open-access research (Thelwall and Kousha, 2015). However, the European Commission has a strategic implementation plan to foster Open Science practice (EOSC, 2019). Also, it has funded European projects to accomplish data/model sharing and standardisation within very large consortia (Blue-Cloud, 2019).

3. AI Applications for blue growth

3.1. Ecological niche modelling

Ecological niche modelling (ENM) refers to a set of computer-based approaches that predict the actual or potential distribution of a species across a geographic area and time. ENM is mostly based on environmental data and aims at identifying the abiotic and biotic conditions that favour a species' subsistence. ENM has been used in conservational biology and ecology, where approaches are categorised as *correlative* or *mechanistic* (Pearson, 2007). While correlative approaches model a species' niche as a function of the environmental parameters, mechanistic approaches use explicit information on the species' physiology. Correlative approaches have used AI techniques to model niche functions, in particular to (i) identify the most relevant environmental data to a species' ecological niche, (ii) simulate niche functions, and (iii) project these functions onto geographical spaces.

Identifying the environmental features correlated to a species' niche requires combining occurrence locations records (i.e. the *presence points* where the species was observed) - and possibly *absence* locations (where the species cannot subsist) - with the environmental parameters of those locations. Before simulating a niche function, the environmental features should be pre-processed and combined to maximise the correlation with the species' preferences. To this aim, processing techniques like Principal Component Analysis and machine learning (e.g. Maximum Entropy and cluster analysis) are commonly used (Coro et al., 2015b; Phillips and Dudík, 2008). Machine learning models are normally used to simulate a niche function, e.g. Generalised Linear Models, Artificial Neural Networks, Maximum Entropy, Support Vector Machines etc. (Coro et al., 2013a; Olden et al., 2008; Pearson, 2007). These models *learn* and simulate the correlation between presence (and sometimes absence) points and environmental parameters as a function with range [0,1]. This function is finally projected onto a geographical area at a specific spatial resolution by applying the learned function to the environmental parameters of that area.

In the context of Blue Growth, AI-based ENM (AI-ENM) approaches have been used in multi-disciplinary EU projects. For example, they have been used to detect the presence of rare species in a particular area as indicators of areas to be protected from fisheries and exploitation (Coro et al., 2013a; Owens et al., 2012). Further, AI-ENM has been used to assess species commonness and absence in marine areas as indicators of biodiversity change in time (Coro et al., 2015c; Pearman and Weber, 2007; Webb et al., 2012). In these cases, the use of AI, and in particular of pattern recognition techniques, was necessary to combine the expertise of conservation biologists with that of data scientists and AI modellers. Indeed, OS-oriented infrastructures have played an essential role in these experiments to (i) foster multi-disciplinary collaboration, (ii) produce results while publishing models as Web services, and (iii) disseminate results to decision-makers (Coro et al., 2016b; Vanden Berghe et al., 2010). AI-based ENM through OS-oriented e-Is is applicable as long as the e-I makes occurrence records - and the environmental parameters associated with these records - accessible to the models. Currently, the produced species distribution maps are of great support to taxonomic studies and are usually associated with species' descriptions in most large taxonomic collections (Froese, 1990).

3.2. Vessel data analysis and fishing activity forecasting

Vessel Monitoring Systems (VMSs) are either physical or virtual electronic systems that enhance maritime security and fishing activity monitoring. Tracking systems, based on information transmitted by on-board GPS (Vessel Transmitted Information, VTI), integrate different transmission technologies that are eventually processed by a computer system (Chang, 2003). These data have Big Data characteristics and require distributed storage systems to be managed and AI modelling for extracting valuable information. One common application based on VMSs is the monitoring of unreported, unregulated, and illegal (UUI) fishing activity (Davis, 2000). For this task, computer systems combine documents with time series information through AI models (e.g. Bayesian models and Artificial Neural Networks) to estimate the type of fishing activity performed by a group of vessels in a particular area and period (Joo et al., 2011; Walker and Bez, 2010). VTI has been used in AI models also to estimate the behavioural response of birds and marine species to commercial fisheries activity (Votier et al., 2010). Other applications have used AI to enhance the precision and reliability of VTI time series, which usually contain gaps and biases (Palmer and Wigley, 2009). Also, other models have combined AI-ENM with VTI to estimate locations with high fishing pressure (Campanis, 2008; Coro et al., 2013a). These methods help the Blue Growth strategy to regulate illegal activity and monitor the exploitation of marine resources. For example, tuna fisheries in the Pacific and Indian oceans produce several times the incomes of all other fisheries combined and involve frequent UUI fishing activity (Lymer et al., 2008). Thus, forecasting VTI time series is helpful to predict future exploitation rates and locations as well as illegal and piracy activity (Hollowed et al., 2011). Methods used in this context include Artificial Neural Networks combined with signal processing techniques (e.g. Fourier Analysis, Singular Spectrum Analysis), which decompose the time series of effort, longitudes, and latitudes into components that represent the essential structure of the time series and project them in the future (Coro et al., 2016a). Open Science technology has been used in these experiments also to gather and share data from VTI repositories (Coro et al., 2013b, Lee et al., 2010). AI-based VTI processing is being included in decision processes and management strategies. Large companies - like Google - are proposing open-access AI-based vessel monitoring systems, through online platforms (Merten et al., 2016). These platforms also promote VTI re-use in AI models to produce indicators for decision-makers. For example, monitoring authorities have used them to evaluate the success of the application of management strategies (Witkin et al., 2016).

Based on time series of annual catch statistics (at land or in the seas), AI methods are more and more used in fisheries to assess a stocks' status, e.g. to estimate the biomass still available for fishing and the yearly sustainable catch. These *stock assessment* techniques are becoming more and more crucial to safeguard the availability of food resources. One parameter estimated by the models is the Maximum Sustainable Yield (MSY), i.e. the maximum catch that can be taken from a commercial species in a specific area (i.e. a stock), so that catch corresponds to repopulation in the next year. Most stock assessment models are statistical models that require a large amount of prior information (Froese et al., 2017; Shepherd and Pope, 2002). However, data-poor models are emerging that rely just upon time series of catch, biomass, and fishing effort, and estimate MSY with comparable accuracy with respect to data-rich models (Froese et al., 2018a). These data-poor models increase the number of people and countries who can independently assess the status of their resources (Froese et al., 2018b). These models usually rely on population dynamics formulations and estimate *life-history* traits of the stock, e.g. the intrinsic rate of growth and the carrying capacity. They are generally computationally intensive, and high-performance models use exhaustive techniques like Markov Chain Monte Carlo methods (Cope, 2013; Froese et al., 2017; 2018a). Some of these models are available through Open Science platforms and support courses and scientists' assessments (Coro et al., 2015a; i-Marine, 2015). Stock assessment models are already considered in decision-making processes, and their results have been debated in political agendas (Oceana, 2017). Indeed, the suggestions deriving from scientific models are being actually considered in management strategies in Europe, with a decreasing compliance gradient from North to South (Froese et al., 2018b).

3.3. Climate change and effects on species' distribution

Climate change is currently one of the most discussed topics in public and scientific agendas. Ecological changes have potentially disruptive effects on many aspects of human life (Boon et al., 2011; Fritze et al., 2008). Climate change also influences species' habitat distributions, especially if coupled with anthropogenic pressure. This combination has already shown adverse effects on species' abundance and biodiversity at the global level (Cheung et al., 2009; SCBD, 2009). Climate change has severe consequences on many ecosystem services that are integral for human well-being, e.g. food, water, leisure, and recreation provisioning (Harley et al., 2006), and are taken into account by the Blue Growth strategy. ENMs have been used to measure the potential impact of climate change on species' habitat distribution. These approaches use forecasts of environmental parameters under different greenhouse gases emission scenarios (Coro et al., 2016c; Fernandes et al., 2013). However, reliable estimates require using complex models and massive computational resources. Thus, they are mostly limited to the near future and to a regional scale. High-quality forecasts of marine-related environmental parameters, combine information of air and ocean currents dynamics with socio-economic factors (under different greenhouse gases emission scenarios). They require high-performance computing systems even to produce regional-scale forecasts (Artale et al., 2010; Gualdi et al., 2013). However, the products of these models are Big Data that can be analysed with OS-compliant technologies and can be reused in ENMs and stock assessment models to analyse trends of ecological change due to climate change, and assess impact on habitat shift, fisheries, and food provisioning (Coro et. al., 2016b). For example, time series analysis and pattern recognition have been applied to environmental parameters forecasts focussing on different global marine areas and oceans (Coro et. al., 2018a). This application has revealed notable properties, for example that (i) the Mediterranean Sea has potentially a standalone "response" to climate change with respect to other areas, (ii) the trends of the Poles are the most representative of global change, and (iii) the current trends are generally negative and alarming in most oceans.

This information is crucial from the Blue Growth strategy point of view since the retreat of polar ice and the deterioration of tropical ecosystems - due to acidification - influence food availability, organism growth, and reproduction. Most of these considerations and reports have been taken into account by the Paris Climate Agreement in 2016.

Pattern recognition techniques have also been applied to extensive collections of ENM models' projections to extract global patterns of habitat shift and biodiversity change, and to assess the impact of climate change on fisheries (Otto et al., 2016; Uhe et al., 2016). OS-compliant technology has demonstrated effectiveness at combining different AI-ENM models with fisheries information while retrieving/harmonising parameters forecasts from extensive collections (Coro et al., 2018b). These models coarsely approximate very complex systems, but the extracted change rate indicators have a significant overlap with human expert assessments. For example, AI models have correctly predicted the increase of species richness of small-body fishes in the North Sea (Perry et al., 2005), a general shift of their latitudinal and depth ranges (Dulvy et al., 2008), and the probable replacement of calcareous corals by non-calcareous algae in high CO2 regions (Bellwood et al., 2004).

3.4. Alien and invasive species

Alien invasive species (AIS) are animals and plants that arrive *somehow* in a non-native natural environment and have severe consequences on the habitats their invade.

These species can settle in the new environment, increase in number, spread in the invaded area and threaten native species and countries' economy (Galil, 2008). High growth and reproduction rate, lack of natural predators, ability to exploit food resources, and tolerance to a wide range of environmental conditions are shared characteristics of the most dangerous species (Yaglioglu et al., 2011). Recent studies indicate that more than 5% of the marine species in the Mediterranean Sea are non-native (alien) and 13.5% are invasive (Galil, 2009; Golani, 2010; Zenetos et al., 2015). Supervising organisations spend considerable effort to monitor and predict AIS spread and avoid economic and ecological disasters. In the Mediterranean Sea, AIS especially enter through the Suez Canal, and their number is continuously increasing (Golani, 2010; Nader et al., 2012). For example, the silver-cheeked toad-fish *Lagocephalus sceleratus* (Gmelin, 1789) has begun the invasion around 2003 and has rapidly invaded all the eastern Mediterranean basin (Akyol et al., 2005; Peristeraki et al., 2006). This pufferfish is extraordinarily poisonous and lethal to humans if eaten, due to a high level of Tetrodotoxin (TTX) contained mainly in the liver and excreted from the skin (Nader et al., 2012; Yaglioglu et al., 2011). It is favoured by climate change because it prefers medium-high water temperature, which also increases its TTX production.

In Turkey, this species has caused a 5 million euros monetary loss between 2013 and 2014 and currently represents 4% of the weight of total artisanal catches (Nader et al., 2012). Further, since 2003 it has caused several episodes of death and severe illness after consumption since fishermen and ordinary people usually cannot identify it (Bentur et al., 2008; Kheifets et al., 2012). According to Blue Growth, it is crucial to detect, prevent, and eradicate this type of AIS. Selective fishing has been proposed as a solution but has not been effective. However, AI models have been used to forecast invasion patterns and thus to guide the development of preventive and corrective actions (Coro et al., 2018a; Pouteau et al., 2011; Sadeghi et al., 2012). In particular, AI-ENMs have been used to evaluate the differences between an AIS native habitat and the invaded region and have used climate forecasts to predict how climate change may facilitate the invasion (Sax et al., 2007; Thuiller et al., 2005). These AI-ENMs use machine learning and statistical models, e.g. Genetic Algorithms, Maximum Entropy, Artificial Neural Networks, and Support Vector Machines (Kulhanek and Bodur, 2011; Peterson, 2003; Sadeghi et al., 2012; West et al., 2016).

Also, they have been combined with economy-related information to assess the potential economic impact of the invasion (Coro et al., 2018b; Ünal et al., 2017). In this context, OS-oriented approaches have demonstrated efficiency in terms of reducing the time for integrating ENMs with economy-related data and effectiveness in building ensemble models (Assante et al., 2019b). Thanks to the reproducible and transparent methodologies implemented, the results have been included in international strategy documents and decision-makers' agendas (FAO, 2017).

3.5. Cross-domain Reuse of Models and Approaches

Open-Science AI models and approaches developed for ecological and climate modelling can be re-used for other scopes of the Blue Growth strategy. For example, they can be used in underwater habitats restoring and for sustainable tourism, through the implementation of tools for scuba-divers (Lucrezi et al., 2018; Palma et al., 2017). These applications can benefit from OS products such as GIS services, ENM species maps, AI-assisted applications, and collaboration tools. For example, OS services have been used to endow scuba-divers with ENM GIS maps in an explored area, and with processes for underwater photo sharing that rebuild an explored area as a 3D model through photogrammetry (Coro et al., 2019a; Palma et al., 2018a, 2018b). Additionally, Web services have been built to offer Virtual Reality tools to explore these reconstructions (Calvi et al., 2017; Coro et al., 2019). These OS services address both scientists who want to monitor the status of an ecosystem (e.g. a coral reef) in time, and tourists who want to plan the exploration of an underwater area and may use the 3D reconstructions to plan further visits. Thus, through OS-compliant platforms, it is possible to re-use models initially conceived for a specific scientific task on a new Blue Growth topic, such as citizen science, which may create financial gain and social benefits.

The Food and Agriculture Organisation of the United Nations (FAO) has sponsored Open Science platforms, and AI-enabled Virtual Research Environments, to support social analyses in marine science (FAO, 2020a, 2020b). In particular, these environments offer solutions to (i) visualise, analyse, and report essential ecological features within marine protected areas, (ii) study human-activity impact on these areas, (iii) monitor aquaculture activity through the automatic processing of Earth observations, (iv) understand aquaculture impact on protected areas, and (v) support maritime spatial planning. Generally, techniques conceived to process Big Data in social sciences have also been proposed to manage Blue Growth topics (Aronova et al., 2010; Palma et al., 2019). The idea behind these approaches is that the management of protected areas can benefit from the complementation of ecological information with social-science analyses regarding environmental economics, tourism, ecosystem-generated services, and the socio-cultural value of biodiversity (Bennett et al., 2017; Gruby et al., 2016; Mascia et al., 2003). Overall, integrating biodiversity conservation with human dimensions is an integral part of the concept of Digital Earth (Gore, 1998; Guo, 2017; Guo et al., 2014), i.e. a virtual representation of the globe that should allow accessing a vast amount of scientific and cultural information, and help people understand the Earth and human activities.

AI models for marine science have also been re-used through OS platforms in entirely different domains. For example, AI approaches assessing marine species commonness have been re-applied as-they-were to rivers restoration, e.g. to identify regions where groundwater mixes with a river's bed (*hyporheic* zone) (Magliozzi et al., 2019). Likewise, Maximum Entropy models for ENM have been re-applied to identify the most suitable sites for a geothermal energy plant installation by treating planting suitability as a species-presence function of environmental parameters (Coro and Trumpy, 2019). These applications were possible thanks to the re-usability guaranteed by the standardisation of data and processes provided by an OS platform, which allows re-applying the models to new data.

4. Conclusions

In this paper, we have presented technology and methods that support the Blue Growth strategy with economic, ecological, and sustainability assets. Artificial Intelligence, combined with Open Science-oriented platforms, can convince decision-makers to include results in their management strategies, thanks to the transparency of the supported methodologies. Thus, a sustainable management of marine and coastal ecosystems can be addressed by combining complementary competencies and approaches through collaborative online tools, and then by openly offering reproducible results to decision-makers. Important features brought by OS-compliant platforms to this context are (i) the transparency of the methodologies through the repeatability and reproducibility of the processes, (ii) the longevity guaranteed to data and processes through platform sustainability plans, (iii) the re-usability of the hosted models across different domains, (iv) the management of Big Data complexity and size, (v) the production of new knowledge as a consequence of the creation of new methodologies.

Overall, the reported examples indicate that AI is supporting Blue Growth in several ways: (i) to simplify complex problems through the discovery of an underlying analytical function defined on the input parameters, (ii) to select important information out of a large set of parameters related to a particular phenomenon, (iii) to estimate the parameters of a function that regulates a complex system, (iv) to produce and discover new knowledge out of Big Data, and (v) to find new virtuous combinations between datasets. One possible drawback is that most AI models do not reveal the rationale behind their outputs (e.g. Artificial Neural Networks, Long Short-Term Memory models, etc.), which often prevents explaining the mechanisms behind the modelled phenomenon. Further, the results are possibly driven by the prior knowledge of the modeller, who pre-selects particular input parameters or introduces *prior* information in variable initialisation (e.g. in Bayesian models). These shortcomings, together with the difficulty to make Open Science practised in every experiment, are hindrances also for Blue Growth development and will be a focus of future research in these sectors.

The future of OS-platforms will likely see AI also used as an e-Infrastructure *meta-model* to improve the cooperation between users. Indeed, an AI model working over an OS-platform can analyse the practices of the platform's users to inform other users about the possible cross-domain applications of their methods and data. This approach would create new collaborative laboratories and focus groups. New knowledge would come out not only from the data owned by the single scientists but also from their practice that – when repeatable and standardised – may be re-used for novel applications. This combination of AI and OS could also help to combine and harmonise the many topics addressed by the Blue Growth strategy itself.

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