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Distribution and abundance of fisheries resources in the archipelago of Berlengas using baited remote underwater videos (BRUV) systems

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VOLUME 1

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I just want to make you proud.

Abstract

Marine Protected Areas (MPA) represent a safe refuge for numerous species of fauna and flora that suffer from the impacts of exploited resource extraction and the ongoing climate change. Amongst these species, some of them represent a substantial part of national food sources and, therefore, their monitoring and management are of extreme importance. The MPA of the archipelago of Berlengas is a very productive region on which many fishermen rely and whose whole income depends on the health of the region. This study aims to determine if the usage of Baited Remote Underwater Videos (BRUVs) could be an effective technique to monitor the area and commercially valuable marine species whilst determining if there is any significant impact of environmental variables on these species, providing evidence-based knowledge to guide more informed fisheries management.

Biological data were collected using a BRUV system. Different environmental variables were preliminarily evaluated before proceeding to a modelling phase (Generalized Linear Models for categorical variables and Generalized Additive Models for continuous variables) for a more robust analysis of the influence of environmental predictors on the abundance and occurrence of the 6 most common species. Species abundance was also evaluated along a transect perpendicular to the shoreline to ascertain the suitability of current MPA spatial design, which imposes fishing restrictions within a 50 m distance from the coast.

The community sampled in this study suggest that resorting to BRUVs to monitor fisheries resources in this area could represent an effective method since the community characteristics were in accordance with previously published research on local biodiversity. The modelling process deemed ‘Tide’ and ‘Rugosity’ as the most influential categorical variables on species abundance, whilst ‘Distance to Shore’ and ‘Depth’ were considered to be influential on one of the analysed species. Transect analysis was only deemed influential for *Diplodus vulgaris*.

Ultimately, this study suggests that BRUVs are a viable monitoring mechanism to assess the distribution and abundance of commercially relevant fisheries resources in MPAs, with a future perspective of real-time monitoring, fed by live data transmission that would be processed with AI systems for automated species identification. To do so, further investigation is required, alongside with a grater sampling effort, to ascertain biological responses to environmental pressing and endowing stakeholders and managers with robust information to guide fisheries activities and resource management.

Keywords: MPAs, Berlengas, BRUV, Statistical modelling, Environmental influence.

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Introduction

Fisheries context

On a global scale, unequivocal threats to marine biodiversity and to the services they provide are taking place. Marine ecosystems are degrading progressively due to multiple factors including overfishing, maritime traffic, invasive species, climate change, among others. These deleterious processes often lead to biodiversity loss, habitat degradation, and changes to marine communities and its structures (Roberts, 1995).

Since the mid 1980's, over 100 million tons of biomass are removed from the ocean every single year. This large extraction of biomass necessarily plays an important role in shaping the structure of marine communities, with both direct and indirect effects being observable. Direct effects include a decrease in abundance and biomass of fish and invertebrate species naturally occurring in the ocean. The collapse of some fish species from the ocean can have a significant cascading effect on marine ecosystems because the removal of predators located higher in the trophic network may unbalance ecosystem structure by allowing their usual prey populations to grow exponentially, which will produce increased pressure on lower trophic levels (Rolim et al., 2022). Most of these predator species need more time to reach maturity and reproduce, which renders them more susceptible to overfishing. Given that marine predators keep being continuously removed from their communities (Pauly et al., 2005), prey populations are expected to grow and disturb the balance of marine communities, carrying considerable consequences to the ecosystem.

Fishing practices go way back in time, with mankind relying on fisheries as a food supply at least for ten to forty thousand years (Squires, 2009). However, fishing practices have drastically changed over the last century, fuelled by technological development. Although there has been a recent optimization to the way they are conducted, fishing practices have been getting progressively more invasive and destructive, producing great damage to marine ecosystem and endangering the sustainability of marine resources (Walsh et al., 2002).

Due to the lack of regulations, enforcement, and economic incentives, some destructive fishing methods continue to be used in various parts of the world including in Portugal. Methods such as bottom trawling and dredging are routinely used in national waters, and they have known deleterious effects by promoting habitat destruction (particularly regarding rocky substrates) and the non-selective removal of bycatch species (Collie et al., 2016). Also, ghost fishing (i.e. lost or discarded fishing gear which continue to catch fish and other animals, promoting the entanglement of these creatures and leading to injury or death) is a known problem in the Portuguese continental platform (Collie et al., 2016).

The Portuguese coastline is extremely vast and superbly rich in fishing resources, which correspond to an important part of the national social and economic welfare. The fish and seafood provided by the Atlantic Ocean form a big component of the renowned Portuguese gastronomical tradition. According to the National Statistics Institute, 5,1% of the Portuguese GDP is provided by the ocean, supported by the 180 thousand tons of fish extracted (INE, 2018), and as so, there are efforts to be made by the government and the people to preserve this source of revenue aiming at ensuring the sustainability of marine ecosystem services and the environmental and socioeconomic benefits derived from a healthy ocean. However, marine resources are threatened not only by overfishing and unethical fishing practices but also by climate change processes which further degrade sensitive ecosystems. This raises several concerns to the national population and to the fishing communities which rely on predictable fish harvest as a food supply and economic revenue.

Climate Change and environmental forcing

Knowing for a fact that every ecosystem is suffering with the effects of climate change, it would be naive to think that the species we consume, or use would be safe, even if mitigating the overfishing threats. Recent simulations under two different scenarios both led to prospections of loss of biomass and, therefore, increased prices of these resources. The continuous rising of seawater temperature and its acidification will cause species to move north, leading to changes in resource distribution which will affect the whole fishing industry (Lam et al., 2012).

Evidence indicates that climate change may result in changes in primary productivity and oceanic circulation patterns, sea-level rises (due to ice melting), and an increased frequency of extreme weather events. All these changes will have impact on the various levels of ecological organization, interfering with all individuals and their communities, which could propagate to the whole ecosystem. (Sumaila et al., 2011).

Around the globe, fisheries are underperforming and have been so for the last decades, not only because they surpassed their maximum sustainable yield, but also because the marine environment and its conditions are on a slope. The physical and chemical conditions of water are expected to affect the productivity of marine fisheries and, along with this, they may lead to severe socioeconomic losses. The species we rely on for food, the fish, and invertebrates we catch, are strongly dependent on oceanographic conditions, and their physiology, growth rates and reproduction patterns are directly affected by the environmental status (Sumaila et al., 2011).

Besides, these species also tend to alter their spatial distribution as an ecological response to climate change. Once they assess that the environmental conditions (e.g., temperature, salinity) no longer match their biological thresholds, they will scatter around for a more suitable place, altering the community structure both at their original distribution areas as well as at the areas where they disperse into. Also, in a fisheries perspective, modifications to the distribution patterns of marine resources may result in economic losses because species will not be available where they traditionally were, prompting fishers to spend more time and fuel seeking for targeted resources (Lam et al., 2012).

Such a scenario is not unprecedented. In fact, there have been times when extreme events significantly altered the environmental conditions of a certain region and impacted fisheries outcomes. For instance, whenever there is an 'El Niño' event, there is a huge decline in the landings of marine pelagic fish. This causes severe impacts in the economical productivity of affected regions, potentially leading to loss of jobs and to decreased home-income and revenues (Lam et al., 2012).

From a biological point of view, the most effective way to prevent impacts of climate change on marine resources is maintaining more abundant populations. Therefore, addressing the overfishing problem is essential. To achieve this, management measures must be taken anticipately, and they should properly take into consideration stakeholders needs while strictly applying the directives they assign to specific areas (Sumaila et al., 2011).

Over the last few decades, there has been a growing interest by environmental managers, politicians, and the scientific community in the potential of certain areas and its resources for promoting marine conservation. This has led to an urge to protect these areas through adaptative and evidence-based mechanisms that will hopefully benefit both marine ecosystems and those who rely on them (Higgins et al., 2008). In order to protect marine biodiversity and promote the sustainable extraction of fisheries resources, it has been established that some areas are to be protected and resource extraction in those areas is to be regulated. These areas are now called Marine Protected Areas (MPAs).

Marine Protected Areas

Multiple strategies to increase ocean resilience to anthropogenic pressure are currently in place, from overfishing control to the establishment of MPAs. The effectiveness of these measures and their importance for biodiversity conservation depends on the compliance, monitoring, and enforcement of governance arrangements that fall on the sustainable extraction of resources (Laffoley et al., 2019).

Recently, there has been a significant expansion of MPAs, defined since 1988 by the International Union for the Conservation of Nature (IUCN) as: "Any area of intertidal or subtidal terrain, together with its overlying water and associated flora, fauna, historical and cultural features, which has been reserved by law or other effective means to protect part or all of the enclosed environment."

Recognizing and protecting special places to sustain wildlife and nurture natural processes is not a new development. The first documented example of an MPA dates back to the late XIX century, in

Australia. After consecutive changes in the legislation, in 1982, when the UN Convention on the Law of the Sea (UNCLOS) took place, the fundamental framework for marine governance was introduced and obliged all countries to protect and preserve the marine environment.

For an area to be considered an MPA by IUCN, conservation must be the primary overarching purpose of the area. Yet, this comprises areas that are highly protected zones, with a strict no-take policy, and multiple-use areas where the removal of resources and their use is allowed, bearing in mind that there are conservation goals that must be achieved.

Therefore, IUCN has established categories according to the policy by which MPAs are ruled, knowing that this will depend on multiple factors such as: area liability, biodiversity value, social and economic importance, cultural matters, and so on. These categories range from category I – possibly a no-go area used for scientific research and monitoring purposes only, where human visitation and its impacts are strictly controlled; to category V - distinct areas with significant value resultant of the interaction of people and nature, that is vital to protect (Laffoley et al., 2019).

The category by which the MPA is ruled not only will have direct impacts on local communities that may depend on the resources of a certain area but will also be deeply linked to the outcome of the management program. The ecological effectiveness of MPA establishment depends on multiple factors, and it will only prove to be helpful if the policies are properly enforced (Laffoley et al., 2019).

The effectiveness of MPAs for protecting any particular species can be influenced by numerous factors. Studies suggest that MPAs are more likely to be ecologically effective if they:

- Are/include no-take areas: No-take areas restore the biomass and structure of fish assemblages and restore ecosystems to a more complex and resilient state. Partially protected MPAs can have some value by restricting specific activities (e.g. banning trawling to prevent habitat destruction), but in general they are not as effective (Edgaret al., 2014).
- Are properly enforced: the overall effectiveness of the MPA usually goes hand in hand with its management and policy enforcements, and there are plenty of cases where the policies drafted for an area are not properly legislated and this leads to an underwhelming overall outcome of the management program (Edgar et al., 2014; Batista & Cabral 2016).
- Are large (>100 km^2): Some studies suggest that individual reserves must be at least as large as the average dispersal distance for a species. The size of an effective MPA will be different for species with different movement patterns since wide-ranging species will be more vulnerable to fishing than highly site-attached species (Edgar et al., 2014; Batista & Cabral. 2016).
- Have been established for more than 10 years: It takes some time for the implemented measures to have an impact in the ecosystem. The species that sustain these communities

have been under pressure for a considerable time and so it is expectable that they will take several years for their abundance to be replenished back to a pre-exploitation state (Edgar et al., 2014).

- Are isolated: There is some uncertainty on why isolation is such an important factor, but the scientific community was lead to believe that this has something to do with the fact that isolated MPAs are generally well demarcated for control purposes and therefore they are more readily recognized by fishers and more easily enforced comparing to coastlines with mosaic of take/no-take areas or even regulations about fishing methods (Edgar et al., 2014; Moura et al., 2014).

Also, species that are more resilient, less mobile, sheltered from major markets, and have a lower market value tend to exhibit more positive responses to protection (Ban et al., 2017).

Increasing the size and number of MPAs is widely regarded as a way to meet ambitious biodiversity and sustainable development goals. Yet, debate still exists on the effectiveness of MPAs in achieving ecological and social objectives (Pendleton et al., 2017). Reduced access to resources, even in the short-term, can create social and economic inequities. If this leads to decreased levels of cooperation among community members, it should be carefully considered in the evaluation of MPA effectiveness (Pendleton et al., 2017).

If we are to get the most out of MPAs as a marine conservation and management tool, we need to make full use of this diversity of perspectives and experiences to understand when and where MPAs can be best used to achieve desired outcomes (Pendleton et al., 2017). Yet, there seems to be an ongoing trend of MPA establishments, on a rushing attempt to fulfil the goals set by the United Nations (target of protecting 30% of the ocean by 2030) which can be justified by its known positive effects.

Several different studies have been conducted in order to evaluate the effects of MPAs on e.g., food security, resource availability, environmental improvement, and biodiversity recovery (Mascia et al., 2010; Pendleton et al., 2017; Rolim et al., 2022). Concerning to fisheries, it has been demonstrated that properly managed MPAs are very important for the fishing sector. Not only they have proven to be effective in restoring and preserving fish stocks, but there is also evidence that the biomass of whole fish assemblages in no-take marine reserves is, on average, 670% greater than the biomass in adjacent unprotected areas, and 343% greater than the biomass in partially protected MPAs (Sala & Sylvaine, 2018). Moreover, there’s a phenomenon called spillover effect, stating that well-enforced MPAs can increase adjacent fishery catches. Although there is little data on the extent of how much this phenomenon could be beneficial, the fact that both larvae and adults of target and non-target species disperse outside of the MPA’s boundaries is expectedly positive for fisheries and for conservation (Pendleton et al., 2017).

Apart from this, MPAs produce clear benefits to the populations that rely on the fishing stocks, otherwise there would not be proper incentives to make them want to comply with the management program. Besides increasing fisheries stocks, healthy marine ecosystems will help supporting coastal, nature-based socioeconomic development, for example concerning the ecotourism industry. Besides, there is evidence that food security, food quality and its properties, generally remained stable or increased following MPA establishment (Mascia et al., 2010). Whenever there is an MPA management program being applied, fishermen and fishing companies must be assured that the quality of the resources they rely on will not decrease. It is of little use that resource availability increases if the economic value of landed resources drops vertically.

As mentioned, no-take MPAs have greatest effects on the recovery of fishing stocks' biomass and abundance. Yet, this does not mean that partially regulated MPAs are worthless. The abolition of destructive fishing mechanisms (such as bottom trawling) will contribute to preserving the integrity of the sea floor and will therefore provide conditions for fish to stay there and increase the genotypic differences within a community, making it more resilient (Sala & Sylvaine, 2018).

Multiple-use MPA's are managed differently, whereas there is a spatial arrangement that promotes different sets of rules and permits for different segments of the area. In these cases, fishing may be abolished in some areas whilst being allowed to occur in other areas, probably with some restrictions.

The promotion of stock resilience provided by properly managed MPAs is connected to the fact that, in these areas, other human impacts will be significantly reduced. Since activities such as industries and the resulting pollution are controlled, the ecosystems will be subject to decreased amounts of stress (Laffoley et al., 2019).

On an environmental level, marine reserves can cause indirect effects that may restore the pristine structure and complexity of the ecosystem once predator abundance recovers sufficiently. While MPAs protect valuable coastal and oceanic ecosystems and the services they provide, their ability to control global climate changes is limited. However, because they provide long-term protection and enable population replenishment, MPAs may be pivotal places to foster resilience against climate change impacts and to provide sentinel sites for science development and environmental monitoring to better understand climate change effects (Laffoley et al., 2019).

Therefore, providing critical information about the condition of the marine environment and the trends of resource abundance is a necessary step towards enhancing MPAs management programs and their effectiveness. Monitoring ecosystems and the communities that compose them is instrumental when assessing the efficiency of management measures and developing optimization strategies (Laffoley. et al., 2019).

Marine wildlife monitoring

Traditionally, marine researchers relied on visual census to monitor the species that constitute marine communities, which has proven not to be as effective as thought because there is a negative effect caused by the behavioural responses of fish to the presence of a diver (Dickens et al., 2011). Also, fisheries data are considered to be an important tool for marine fauna monitoring. The quality of these data, however, present several issues related to fishermen following the target species and thus producing biased results which are not representative of the whole scenery.

More recently, technological advances provided us with new techniques to acquire data on marine fauna distribution and abundance which preclude any biases resulting from a divers' presence in the water or from fisheries intrinsic practices.

Baited Remote Underwater Video systems (BRUVs) are becoming increasingly more popular to assess the effects of both climate change on fish assemblages and the structural complexity of marine habitats, but also to assess how MPA management frameworks influence aquatic fauna and flora. As a remote technique, it efficiently detects vagile fauna that would otherwise flee in the presence of an approaching diver. Also, it can be operated in deeper areas compared to how deep a diver could go, whilst it is easily replicable due to its most efficient cost-benefit ratio, which is very attractive. Moreover, the resulting images also provide valuable information to better categorize marine habitats and their intricacies. Factors such as depth and topographic complexity have shown to be the among the most influential physical factors shaping the structure of fish assemblages (Roberts et al., 2002). BRUV systems, however, are highly dependent on water condition since it will directly impact the visibility and, therefore, the ability to identify focal species in video samples. Also, a proper monitoring study will generate a lot of hours of video samples that will consume considerable time to be thoroughly analyzed. In that account, recently emerged computation with artificial intelligence (AI) provides a solution to this issue, since the development of a software capable of identifying species by itself would enable the autonomous monitoring of an MPA, endowing researchers, managers, and stakeholders with evidence-based information guide decision-making processes.

This autonomous monitoring program would be useful for tracking the performance of multiple-use MPAs over the long term and enabling real-time management. However, it is first necessary to demonstrate that this method it capable of remotely sample marine fauna, as this component is essential to support the development of a fully autonomous system for monitoring marine species in areas of particular interest, such as MPAs.

General Aim

The fundamental aim of this study is to evaluate the effectiveness of the BRUV technique in sampling commercially valuable bentho-pelagic species in a multiple-use MPA. Such knowledge is useful to derive potential programs aimed at autonomously monitoring the distribution and relative abundance of marine taxa including fisheries resources.

Specific objectives:

More specifically, this study aims at:

- Assessing the species composition of commercially relevant fauna sampled with BRUV in a multiple-use MPA to explore the hypothesis that this technique is suitable for monitoring fisheries resources in areas of particular interest.
- Evaluate the influence of environmental traits on the distribution and abundance of fisheries resources.
- Compare species abundance at varying distances from shore to assess the suitability of the currently designated no-fishing area around the island up to 50 m from shore.

Methodology

Study Area

The Berlengas Archipelago is situated 5,7 miles off the coast of Peniche (more specifically Cabo Carvoeiro) and is constituted by three sets of Islands: Berlengas, Farilhões and Estelas (Fig. 1). It was constituted a Nature Reserve in 1981, aiming to preserve the biodiversity and ecosystems off the region, whilst still providing for the local communities and general public. The Berlenga Island is the largest of the group and the only island open to visitation, thus being the one that experiences more anthropogenic pressure.

Figure 1 - Berlengas Archipelago.

The Berlengas Archipelago is notorious because of the diversity of marine species that can be seen and captured (which of course attracts a lot of fishermen and tourists). The reason behind this is that it is located near the southern and western margins of the Nazaré Canyon. This deep-sea canyon is responsible for intense seasonal upwelling, increasing the productivity of the region and therefore the number of prey and predators (Inglês, 2010). This phenomenon is intensified by the strong northwestern winds that are originate from the warm Portugal current that flows southwards along the Portuguese coastline (Inglês, 2010).

The marine reserve seabed is extremely complex. There are long sandbanks between granite rock structures covered in algae and sessile invertebrates that provide sheltering and food for many species, thus supporting their life cycles. Moreover, there is a distinct occurrence of submerged and partially submerged caves that contribute to the singularity of the region, as so to the need of properly conserving and monitoring them (Vasco-Rodrigues et al, 2011).

This region is an ecological asset and all the marine area surrounding the islands has an important biological value associated to it. Besides, the islands themselves are very important for the environment, harbouring some endemic plant species and colonies of seabirds which use the area to breed or rest while performing latitudinal migrations (Inglês, 2010).

Marine Reserve Development

In order to better preserve this ecosystem, in September of 1981, the main island of Berlenga and the surrounding isles, as well as the ocean around them (up until 30 meters from the coast), were designated as a Natural Reserve, thus being legally protected and monitored. In 1998 there was a reclassification of the Reserve, widening the oceanic area under protection (Vasco-Rodrigues et al., 2011).

As the century was coming to an end, there were more measures coming to life. The region was defined as a SPA (Special Protection Area) for bird species and then integrated as part of the Natura 2000 network, granting it some more socio-economical value and protection. Later that year, the very important fishing sector became more regulated. The measures, firstly implemented in 1990, got stricter and prevented fishermen to harvest, for instance, barnacles in some places and sometimes of the year. The legal amount that they could catch was reduced and so was the number of licences, an important measure since recreational harvesting got forbidden.

On the 24th of September of 2008, the Minister Council drafted a new planning and management program for the Berlengas Natural Reserve, the PORNB (Plano de Ordenamento da Reserva Natural das Berlengas – translates to Planning Plan for the Berlengas Natural Reserve) - (*Diário da República, 1ª série — Nr. 228 — 24 de Novembro de 2008).*

The marine area of the Berlengas Natural Reserve (BNR onwards) is an important part of the program since its preservation is a priority (Amado et al., 2007). Therefore, there are different levels of protection and prohibitions by which the area was divided (Figure 2):

- **Partial protection zone (type I):** Referring to spots with valuable biodiversity indexes and landscapes, that are known to be moderately/highly vulnerable. Seasonal prohibition of fishing practices in some parts of the area as well as fishing with longline vessels within a 50-meter distance of shore.

- **Partial protection zone (type II):** Buffer area mostly associated with transitional zones since their protection is mandatory to preserve the entirety of the ecosystem. In this area, however, the main goal is to appraise traditional activities, whilst trying to promote the sustainable use of resources.
- **Complementary protection zone:** Wider area that include impact damping zones, with a clear purpose of remodelling the traditional activities, promoting the maintenance of the conservational state of the area whilst trying to promote to a social and economic development.

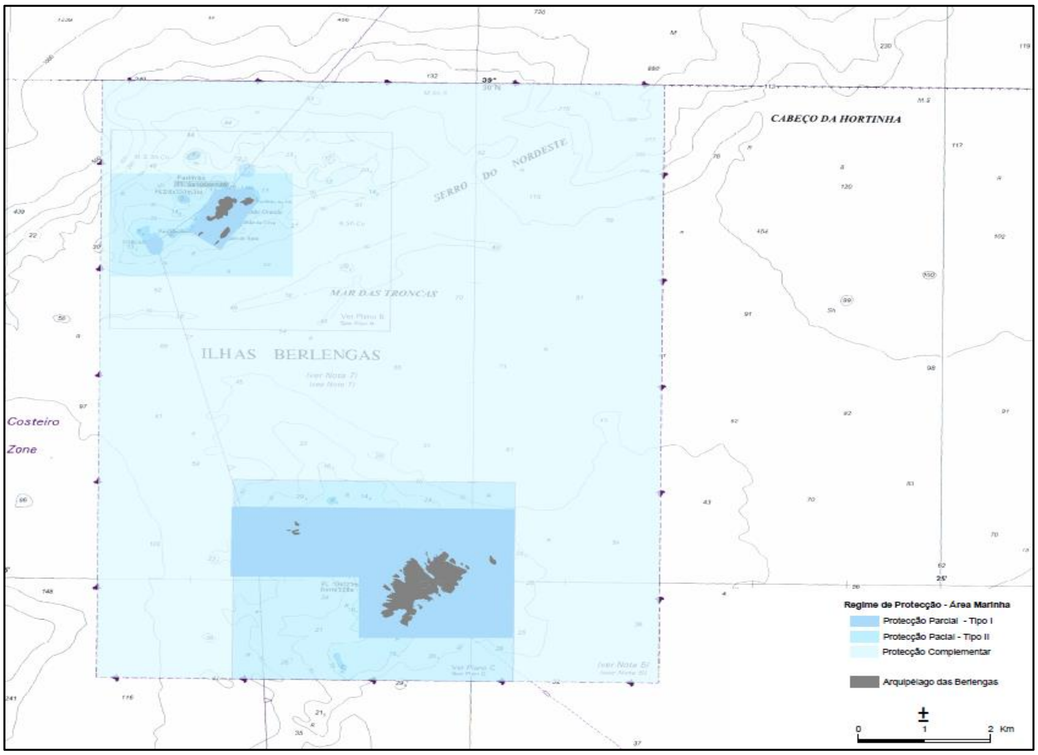


Figure 2- Different protection zones in the Berlengas Archipelago. The darker to lighter blue gradient represents the 3 level of protection (type I, type II and Complementary zone, respectively).

There are plenty of regulations to be applied in each zone, but there are a set of rules that are mandatory, no matter the level of protection. The capture and maintenance of any specimen of marine mammals, seabirds including migratory species, sea turtles, or dusky groupers (*Epinephelus marginatus*) is forbidden, along with the introduction of exotic species. Using noisy means of transportation is also forbidden, as well as the eviction of non-treated effluents or residues into the ocean (Amado et al., 2007).

Therefore, the local fishing communities have adapted to follow the implemented legislations. The most common technique (using anchored longlines) allows fishermen to have rotational fishing targets - seabass, meagre, John Dory, conger (Oliveira, N. et al., 2010), hence making them nondependent of a single species. Also, it constitutes a very sustainable practice, that does not damage the fish, which consequently grants them a higher price (Oliveira, N. et al., 2010).

Baited Remote Underwater Videos systems

In this study, BRUV systems were used to collect biological data on local biodiversity and species distribution and abundance.

BRUV deployments were conducted under the scope of project Anzol+ (Oliveira et al., 2023) between the 1st of June of 2021 and the 27th of May of 2022. The "Anzol+" project started in 2019 with the purpose of creating a system for valuing the fishery products caught within the area of the BNR. The project consisted of evaluating hook and line fishery by small fishing vessels, thus contributing to a better knowledge of these practices and to a more efficient management of BNR resources (Oliveira et al., 2023).

BRUVs are simply underwater video cameras fitted to a hard structure comprising a bait target to which free-ranging fauna will be attracted to, thus providing video samples of species occurrence and abundance at selected sites. The BRUV structure consisted of a four-legged metal pyramid to which weights were added to increase the stability of the mechanism. To this pyramidal frame, a one-meter-long stainless steel pole was attached. In the distal extreme of the pole, some bait (either chub mackerel, *Scomber japonicus*, or sardine, *Sardina pilchardus*) was placed inside a small PVC cylinder with several holes on it to allow the scent of the bait to flow out. Occasionally, bait was placed inside a mesh bag which was tied to the PVC cylinder in such a way that it would be hanging freely beneath the BRUV's pole. On the top of the frame, a video camera (GoPro 8 Hero Black) was installed so that its field of vision would be centred on the bait so that species moving towards the bait would be promptly recorded by the video camera. All BRUVs were deployed from a boat and lowered with ropes attached to a visible surface buoy for easening the retrieval of the sampling gear.

Along with the deployment of cameras, some physical characteristics of the area (Depth, in meters; Temperature, in ºC) were measured with the boat's SIMRAD echo sounder. Afterwards, some other variables were evaluated resorting to a set of different sources (Table 1):

Table 1 - List of utilized sources to evaluate both continuous and categorical variables, for posterior tendency evaluation on the abundance of species.

Variable	Platform (Website)
Tide	Instituto Hidrográfico (https://hidrografico.pt/m.mare)
Moon	Tábua de Marés (https://tabuademares.com)
Wind Intensity	Weather Underground (https://wunderground.com)
Wind Direction	Time and date (https://timeanddate.com)
Surface Temperature	Copernicus Marine Service (https://data.marine.copernicus.eu)

Data sampling

In each day, three BRUVs were simultaneously deployed at previously defined sites, which were selected after interacting with local fishermen to identify the most representative fisheries hotspots in the region. After sampling, a second deployment of the three BRUVs was conducted in the region of the first sampling, following a transect perpendicular to the island where BRUVS were deployed at increasing distance from the shore (i.e., at 50, 150 and 250 meters from shore).

All the deployments occurred during daytime and the videos were cropped to 60 mins since the moment that the BRUV structure landed on the seafloor. Each video was reviewed and analyzed by two independent observers.

Several species of commercial relevance which were recorded by the video cameras were not considered in this analysis. The BRUV system was built to monitor benthopelagic species, meaning that we only accounted for species that live or feed near the bottom as well as in midwaters. Setting bait on the seafloor attracted these species, but the detection of more pelagic species like sardines (*Sardina pilchardus*) and horse mackerel (*Trachurus trachurus*) was merely occasional and therefore was not considered. Also, this study aims to have a better understanding of the relative abundance and distribution of the fishing stock species in the BNR. As so, species with no commercial value like the mediterranean rainbow wrasse (*Coris julis*) were not contemplated.

For each BRUV sample, the maximum number of individuals (MaxN) of a certain species was recorded. This estimate was taken as the maximum number of individuals simultaneously sighted in a single video frame, or the maximum number of individuals that could be otherwise identified due to particular body marks or movements around the camera field of vision which were judged to be incompatible with observations from a single individual. Hence, MaxN represents at the most an under-representation of species abundance in each sample.

Besides, we also took notes if the sampling set was tilted (i.e., if the camera ended up facing the sea surface or sea bottom, which could result in more pelagic or more demersal species being sampled, respectively). Also, we classified water visibility in each video sample since it could have a practical effect on the ability to detect and identify species, and we recorded whether an external bait was used because it could have an effect on species responsiveness towards the BRUV.

We also recorded the type of substrate as soft, mixed, or hard substrate, and the rugosity of the seafloor from highly complex (e.g. conspicuous rocky formations) to monotonous (sandy flats) in order to determine if there were any correlations between these factors and species abundance.

Statistical Analysis

We proceeded to determine whether environmental variables (both categorical and continuous) had any influence over species occurrence and abundance. First, species with less than five sightings were excluded from the analysis. Then, we determined that the maximum number of zeros allowed in our data set (i.e., the maximum number of deployments where species were absent) would be 85% (i.e. species had to be identified in at least 15% of the sampling sets). The final list of eligible species was comprised of only 6 species, namely the sea bass (*Dicentrarchus labrax*), the white seabream (*Diplodus sargus*), the two-banded seabream (*Diplodus vulgaris*), the zebra seabream (*Diplodus cervinus*), the black seabream (*Spondyliosoma cantharus*) and the common octopus (*Octopus vulgaris*).

Initially, boxplots were generated to visualize the distribution of species abundance across each environmental variable. Correlation tests were conducted to each pair of environmental variables to determine if these were correlated, since correlated covariates should not be simultaneously included in the same model. We used Pearson's correlation tests to measure the strength of linear correlation between two continuous variables (by dividing their covariance by their standard deviations) (Faizi & Alvi 2023).

Three potentially confounding variables (i.e., Tilt, Exterior Bait and Visibility) where tested individually beforehand to assess whether they showed any influence on fish abundance measurements. These variables could potentially generate sampling artifacts in the analysis if their effects were not accounted for because they can influence the amount and type of individuals sampled. A tilted setup could, for instance, point towards the surface and thus record species that are strictly pelagic. Visibility is deeply associated with turbidity, whereas intense levels of turbidity would compromise the identification process. External bait could have a skewing effect on the results, since the movement of bait could be more attractive to some species than others. The elaboration of separate Generalized Linear Models (GLMs) for each of these variables, enabled the confirmation of which, if any, of the three had influence on the visualization process. After choosing the error distribution family (between zero-inflated, poisson, and negative binomial) by comparing the associated Bayesian Information Criterion (BIC) of each family, the modelling process went on to determine if the variable had an associated p-value below the 0,05 threshold and therefore had influence in the process.

The effect of categorical environmental variables on species abundance (herein defined as MaxN) was analysed using GLMs, since the data violated assumptions of normality and homogeneity of variance. GLMs of environmental variables were built using a forward stepwise selection procedure. This method consists of starting with the null model with no predictors and then testing the addition of each individual variable in the model, where a pre-defined model fit criterion will inform the best performing predictor. Then, the inclusion of a second predictor is tested across all remaining predictor variables and evaluated, and this process is repeated until the inclusion of new predictors does not improve the model to a statistically significant extent. *A priori*, we designed six separate GLMs with different error distribution families (poisson, negative binomial and zero-inflated) and link functions to identify the most adequate distribution to our data. Model selection was based on Bayesian Information Criterion (BIC), with the lowest BIC value being considered the best performing model. BIC was chosen instead of AIC because the former proved to be more conservative than the Akaike Information Criterion (AIC), which frequently led to non-significant statistical results. In most cases, we proceeded with a negative binomial error distribution and a log-link function.

For each eligible species, we proceeded to draft the null model with the chosen error distribution family and link function, that we would then compare with a more complex model with one predictor variable. The significance of the difference between the simpler model and the more complex one was assessed with a Vuong's closeness test. This test compares the likelihood of the two models and evaluates whether one model significantly outperforms the other in terms of fitness. If the resulting p-value was lower than 0,05, the models were significantly different and we would thus select the more complex model, otherwise the simpler model would be selected. In the former case, we would proceed to design a more complex model with two predictors after removing the predictor previously used from the list of candidate predictors. We would then compare this model with the simpler one and would keep the model with lowest BIC value. Then, the whole procedure was repeated until the inclusion of new predictors did not improve the fitness of the model. The final model with lowest BIC among all candidate models for each species would represent the predictor variables which more effectively explained the variation in species abundance. Model coefficients and 95% confidence intervals were then generated. Finally, model diagnosis was conducted to examine the compliance of final models with their assumptions.

In the cases where the model selection procedure was unable to select a predictor which would outperform the null model, we performed complementary Kruskal-Wallis tests to detect significant differences in species abundance across the levels of environmental variables. Even though this method is not as reliable and informative as GLMs, it provided some information about the potential impact of these variables on the abundance of the selected species.

Since our data set comprised a relatively small number of samples, we conducted a complementary approach to examine the occurrence (i.e., the presence or absence) of eligible species using a binomial GLM. Through a similar forward stepwise procedure (in this case, using a negative binomial error distribution error family), we were able to determine the effect of the same categorical variables on the occurrence of the species.

Additionally, we also designed models that concerned continuous variables (depth and distance to shore). In this case, we used GAMs (Generalized Additive Models) that would, separately, assess the effect of these variables on each of the 6 species, by using them as independent variables and the specie's abundance as the response variable. After testing, we were able to determine which of the error distribution families suited our models the best. The visual representation of the final model (and the associated p-value) allowed us to perceive if there were any effects of these variables on species abundance

Species abundance was also evaluated according to its variation along a transect perpendicular to the shoreline. Some of the deployments were conducted along a transect, with sampling points at 50, 150 and 250 meters from shore. A GLM model was designed to compare each of the defined distances, possibly leading to conclusions and suggestions about whether the 50 m 'no-fishing zone' was adequate.

The R software version R-4.3.2 was used for all analyses, with packages *MASS* to run negative binomial models (Venables & Ripley 2002), *pscl* to run zero-inflated models (Jackman. 2024), *nonnest2* to perform comparative tests between the designed models (Merkle, et al., 2016) and the *mgcv* package for GAMs (Wood. 2020). Statistical significance was set at $p < 0.05$.

Results

Sampling analysis

A total of 49 BRUV deployments were conducted, from which the first was discarded since it was a test to see if the mechanism was properly set. The remaining 48 BRUV deployments were conducted between January 6th of 2021 and May 27th of 2022. Each sampling day, three BRUVs were simultaneously deployed around a pre-selected site known by fishers as good fishing spots (Figure 3), at distances from shore ranging from 46 to 2198 meters. Posteriorly, a second deployment was conducted by placing the three BRUVs along a transect perpendicular to the shoreline, with the first BRUV being placed at 50 m from shore, the second BRUV being placed at 150 m from shore, and the third BRUV being placed at 250 m from shore, so that the three BRUVs would operate at a 100 m distance from each other.

Figure 3 - Sampling points of BRUV deployments around Berlengas, divided by sector (Sector 1 – Red; Sector 2 – Blue; Sector 3 – Yellow; Sector 4 - Green).

The environmental variables collected during BRUV sampling are presented in the appendix section (Appendix – Supplementary table 1).

The BRUVs were placed on the seafloor, in depths ranging from 13 to 42 meters, mostly on hard and rugose substrates that often led to moderate tilts.

Concerning the sea conditions, the deployments were conducted during both ebb and flood tides under visibility conditions that never reached the level 3, denoting suboptimal visibility.

The atmospheric conditions were taken very seriously into consideration since bad weather would make the viewing process much more difficult. Therefore, all deployments were made under good weather conditions. An example of this is the fact that wind speed was always below 19 km/h, which means that it was never more than what is defined as a gentle breeze under the Beaufort wind force scale.

Descriptive analysis

A total of 28 bentho-pelagic species with commercial value belonging to 17 different families were observed during the study period (Table 2). Sparidae was the most represented family, with a total of 6 species, followed by Carangidae and Rajidae, both with 3 species each. Besides the Serranidae family (with 2 species), all the 13 other families were represented by a single species (Appendix – Supplementary figure 1).

As for the overall abundance (N) of each species (i.e. the number of individuals that were positively identified), the seabass (*Dicentrarchus labrax*) was the one with a larger number of individuals sampled, with an estimated number of 780 fish. On the other hand, some species like the endangered *Epinephelus marginatus* were only identified once. Amongst the visualized species, some of them had high commercial value such as the white grouper (*Epinephelus aeneus*), the conger (*Conger conger*), the small-spotted shark (*Scyliorhinus canicula*), the common squid (*Loligo vulgaris*) and the European lobster (*Homarus gammarus*).

Also, shoals of seabass (*Dicentrarchus labrax*) or pouting (*Trisopterus luscus*) were visualized and represent a considerable resource.

Due to the selected abundance and occurrence thresholds, the species that proceeded to analysis were *Dicentrarchus labrax, Diplodus vulgaris, Diplodus sargus, Diplodus cervinus, Spondyliosoma cantharus* and *Octopus vulgaris.*

Table 2 - Species diversity and overall abundance (N) of marine fauna sampled with baited remote underwater videos in Berlengas.

FAMILY	**SPECIES**	**N**
Sparidae	*Diplodus cervinus*	14
	Diplodus sargus	71
	Diplodus vulgaris	283
	Pagrus pagrus	4
	Spondyliosoma cantharus	9
	Sarda salpa	61
Carangidae	*Caranx rhonchus*	9
	Pseudocaranx dentex	6
	Seriola rivoliana	52
Rajidae	*Raja brachyura*	1
	Raja clavata	5
	Raja ondulata	2
Serranidae	*Epinephelus aeneus*	7
	Epinephelus marginatus	1
Balistidae	*Balistes capriscus*	3
Congridae	*Conger conger*	7
Gadidae	*Trisopterus luscus*	112
Moronidae	*Dicentrarchus labrax*	780
Mullidae	*Mullus surmuletus*	4
Muraenidae	*Muraena helena*	3
Scyliorhinidae	*Scyliorhinus canicula*	8
Triglidae	*Chelidonichthys lucerna*	5
Zeidae	*Zeus faber*	7
Octopodidae	*Octopus vulgaris*	10
Loliginidae	*Loligo vulgaris*	1
Nephropidae	*Homarus gammarus*	1

Note: small pelagic fish and species of no commercial value were not included in the study.

Statistical analysis

A Pearson product-moment correlation analysis to evaluate the existence of correlations between continuous variables provided the following results (Table 3). The 0,05 p-value threshold suggests a correlation between surface temperature and depth, with a negative influence of -0,350. Also, a negative correlation between distance to shore and wind intensity was determined, even though it sustained a less meaningful correlation index, -0,293.

Table 3 - Correlation analysis between continuous variables. (t = t-test statistic, Df = Degrees of freedom, p-value, 95% confidence interval, Correlation index)

Variable A	Variable B	t	Df	p-value	2,5%	97,5%	correlation
Surface temperature	Wind intensity	-0,547	46	0,587	-0,356	0,209	-0,080
Surface temperature	Distance to shore	-0,982	46	0,331	-0,411	0,147	-0,143
Surface temperature	Depth	-2,532	46	0,015	-0,577	-0,073	-0,350
Distance to shore	Depth	1,590	46	0,119	-0,060	0,481	0,228
Distance to shore	Wind intensity	-2,075	46	0,044	-0,532	-0,009	-0,293
Depth	Wind intensity	-0,202	46	0,841	-0,311	0,257	-0,030

The effect of physical habitat traits on the six species previously enounced was evaluated with an initial set of tests, that would separately evaluate each variable's interference on species abundance. We then proceeded to design Generalized Linear Models (GLM) that allowed us to determine which of the categorical variables had a more prominent effect on the abundance of each eligible species. The results achieved for each of the six species are presented below.

European seabass (*Dicentrarchus labrax*)

Visual inspections of the distribution of seabass abundance across environmental variables suggested that most variables had little effect on seabass abundance, although the type of substrate may have some effect since there were no recordings of this species on mixed or soft substrates (Appendix – Supplementary figure 2e).

<u>Abundance analysis:</u>

The preliminary analysis of potentially confounding variables indicated that two variables had some influence on seabass abundance, i.e. visibility and exterior bait (Appendix - Supplementary table 2). However, only 'Visibility' was used as a weighing factor because the presence of 'Exterior Bait' had a significantly negative effect on seabass abundance, which should not have any biological meaning since it is extremely unlikely that seabass would be repelled by the use of external bait.

Therefore, we ascribed this effect to a sampling artifact where seabass was present by chance only in the more numerous samples with no external bait.

Using ‘Visibility’ as a weighing factor, the model selection procedure was conducted and the model that included ‘Rugosity’ as a single explanatory variable presented the lowest BIC value. Adding a second predictor did not improve the performance of the model (table 4). Additionally, this model had a lower BIC value than the null model (124,684).

Table 4 - Model selection procedure suggesting that Rugosity had the most explanatory variable with 'Visibility' acting as weight variable for the abundance of *Dicentrarchus labrax*. (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion)

Variable 1	**Variable 2**	**AIC**	**BIC**
Tide	-	117,817	123,367
Moon	-	117,840	123,390
Sunlight	-	122,688	130,088
Wind Direction	-	122,275	129,676
Substrate	-	121,423	128,824
Rugosity	-	113,861	**121,262**
Rugosity	Tide	111,084	124,335
Rugosity	Moon	108,221	127,472
Rugosity	Sunlight	112,107	123,208
Rugosity	Wind Direction	111,682	124,783
Rugosity	Substrate	112,464	123,565

However, rugosity turned out to exhibit non-significant p values (p = 0,995 and p = 0,997 for Rugosity levels 2 and 3, respectively), indicating that there was no influence of this variable on seabass abundance. Therefore, we proceeded with the second lowest BIC value, associated with the model using ‘Tide’ as single explanatory variable. This model was kept, and a Vuong test demonstrated that it was significantly different from the null model (p-value = 0,001). The output of the final model is depicted in Appendix - Supplementary table 3, where it is observed that seabass abundance in our samples tends to be significantly (p = 0.001) greater during ebb tides than during flood tides. However, model diagnostics showed that the model did not perform so well (Appendix – Supplementary figure 14a).

The influence of depth and distance to shore was evaluated using generalized additive models (GAM). The generated models suggested that sea bass abundance was not related with neither depth nor distance to shore (Appendix - Supplementary table 4).

The analysis of the effect of distance along the defined points of a transect allowed us to state that, for *Dicentrarchus labrax*, there was no significant difference in species abundance between the transect points since the resulting p-values were all > 0.05 (Appendix - Supplementary table 5).

<u>Occurrence analysis:</u>

The preliminary analysis of potentially confounding variables indicated that there was no influence of these variables in the identification process, since they all present a p-value > 0,05 (Appendix - Supplementary table 2).

The model selection results (table 5) point towards a single explanatory variable model. The lowest BIC value was the one referring to the model that used Rugosity as a predictor, yet the BIC value was higher than the one associated with the null model (50.198). Additionally, the Vuong test performed to compare the suggested and the NULL models point out that they are not distinguishable enough to consider the 'Rugosity' model to be more feasible (p-value = 0,183). As so, the null model was considered as final (Appendix - Supplementary table 3).

Table 5 - Model selection procedure suggesting that Rugosity had the most explanatory value for the occurrence of *Dicentrarchus labrax* (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion).

Variable	**AIC**	**BIC**
Tide	50,325	54,068
Moon	50,190	53,933
Sunlight	51,303	56,917
Wind Direction	45,995	55,351
Substrate	50,531	56,144
Rugosity	46,655	**52,268**

Two-banded seabream (*Diplodus vulgaris*)

Descriptive analysis suggested a relation between substrate type and the abundance of *Diplodus vulgaris*, with greater abundances being observed in rocky and mixed substrates in detriment of sandy substrates (Appendix – Supplementary figure 3e). Additionally, an increased rugosity of the substrate seems to promote greater abundances of this species (Appendix – Supplementary figure 3f). The other variables do not seem to be related with *D. vulgaris* abundance.

Abundance analysis:

The preliminary analysis of potentially confounding variables suggested that there is an influence of Visibility on the sampling process of *D. vulgaris* (Appendix - Supplementary table 2). Since the estimate is a negative value, one can assume a negative effect of worse visibility levels on the abundance of *Diplodus vulgaris*. Therefore, the modelling process was conducted using this variable as a weighing factor.

The model that used 'Tide' as a single explanatory variable presented a lower BIC value than the other candidate models, even after the inclusion of a second variable in the model. The inclusion of other variables led to higher BIC values (table 6), which means that the model with solely 'Tide' as an explanatory variable is more accurate and elucidative of the reality, since it presented a lower BIC value than the null model (266,760). The Vuong test proved that the suggested model is significantly different from the null model (p = 0,012) The final model's results were generated (Appendix - Supplementary table 3) and exhibited a statistically significant p-value for the effect of tide, with ebb tides promoting a greater abundance of *D. vulgaris*. The diagnostic plots for this model (Appendix – Supplementary figure 15a) showed that the model conformed with its assumptions satisfactorily.

Table 6 - Model selection procedure suggesting that Tide had the most explanatory value for the abundance of *Diplodus vulgaris* (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion).

Variable 1	**Variable 2**	**AIC**	**BIC**
Tide	-	259,812	**265,426**
Moon	-	264,020	269,634
Sunlight	-	259,683	267,168
Wind direction	-	265,609	276,836
Substrate	-	264,477	271,962
Rugosity	-	260,225	267,710
Tide	Moon	261,085	268,569
Tide	Sunlight	259,120	268,476
Tide	Wind direction	264,528	277,627
Tide	Substrate	263,145	272,501
Tide	Rugosity	259,398	268,754

The GAMs to test the influence of depth and distance to shore on *D. vulgaris* abundance suggested that there was no relation between none of these factors and the abundance of this species, which was supported by p-values of 0,696 and 0,107, noting that both are above the 0,05 threshold (Appendix - Supplementary table 4).

The analysis of *D. vulgaris* abundance along the transect points revealed that it tended to be greater at a 150 m distance from shore compared to the reference level (i.e., 50 m distance from shore) (Appendix - Supplementary table 5).

<u>Occurrence analysis:</u>

The preliminary analysis of potentially confounding variables indicated that none of the three evaluated variables had a statistically significant influence on the sampling process and therefore should not be considered (Appendix - Supplementary table 2).

The modelling selection procedure selected 'Tide' as the most relevant variable to explain the variability in the occurrence of *Diplodus vulgaris*, with BIC value being lowest for this single predictor than for any other predictor or combination of two predictors (table 7), including the BIC value of the null model (31.407). After identifying the best candidate model, its outputs rendered non-significant results. Since the candidate model with second lowest BIC had the same issue, as well as all the remaining candidate models, we concluded that no candidate model would be useful and the null model was deemed final (Appendix - Supplementary table 3).

Table 7 - Model selection procedure suggesting that Tide had the most explanatory value for the occurrence of *Diplodus vulgaris* (AIC - Akaike Information Criterion, BIC = Bayesian Information iterion).

Variable 1	**Variable 2**	**AIC**	**BIC**
Tide	-	26,652	**30,395**
Moon	-	31,536	35,279
Sunlight	-	27,291	32,905
Wind direction	-	34,143	37,875
Substrate	-	32,007	37,620
Rugosity	-	31,561	37,175
Tide	Moon	28,594	34,207
Tide	Sunlight	25,315	32,800
Tide	Wind direction	32,196	43,423
Tide	Substrate	30,325	37,810
Tide	Rugosity	29,914	37,399

White Seabream (*Diplodus sargus*)

There seems to be a correlation between the abundance of this species and the substrate type since no individuals were identified in soft substrate, pointing towards a possible preference of *Diplodus* *sargus* for hard substrates (Appendix – Supplementary figure 4e). Likewise, there is a clear tendency for this species to prefer more complex habitats with higher rugosity instead of less complex substrates.

Abundance Analysis:

The preliminary analysis of potentially confounding variables suggested that there is an influence of Exterior Bait on the sampling process, as indicated by a p-value < 0,05 (Appendix - Supplementary table 2). Due to the fact that the estimate is positive, one can assume a positive impact of this variable on the abundance of white seabream. Proven this, the developed models included 'Exterior Bait' as an obligatory covariate to account for the effect of this variable on species abundance. The model selection procedure indicated 'Rugosity' as the variable that had a greater impact on shaping the abundance of *Diplodus sargus* (table 8), considering that the BIC value of the selected model was lower that the null model's BIC (156,076).

Table 8 - Model selection procedure suggesting that Rugosity had the most explanatory variable with 'External Bait' acting as weight variable for the abundance of *Diplodus sargus*. (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion)

Variable 1	Variable 2	AIC	BIC
Tide	-	151,886	157,500
Moon	-	152,532	158,146
Sunlight	-	144,688	152,173
Wind Direction	-	140,622	151,849
Substrate	-	144,209	151,694
Rugosity	-	142,133	**149,618**
Rugosity	Tide	143,970	153,326
Rugosity	Moon	143,830	153,186
Rugosity	Sunlight	140,932	152,159
Rugosity	Wind Direction	138,469	153,439
Rugosity	Substrate	143,325	154,552

Results for the Vuong test indicated that the selected model was significantly different than the null model (p = 0,019). According to the output of this model, the abundance of white seabream tended to increase with increasing habitat rugosity (Appendix - Supplementary table 3). Despite so, the diagnostics of the model suggested some lack of performance (Appendix – Supplementary figure 16a), even though the p-values for Rugosity (levels 2 and 3) were low, which endows reliability to the model.

The GAM analysis to test the influence of depth revealed a significant ($p = 0{,}010$) effect of this variable on the abundance of *Diplodus sargus*, (Appendix - Supplementary table 4) with depths greater than 24 m producing a negative effect on species abundance (Appendix – Supplementary figure 22c).

The plot indicated that the model fit was reasonable (Appendix – Supplementary figure 22c). However, it should be noted that the model was resolved with only one effective degree of freedom, resulting in overlapping confidence intervals.

The GAM to test the effect of distance to shore on developed to relate the abundance of *Diplodus sargus* resulted in a p-value > 0,05, meaning that there is no apparent relation between the two variables.

The analysis of the effect of distance from shore along the transect points on *Diplodus sargus* abundance rendered non-significant p-values (Appendix - Supplementary table 5), indicating that the abundance of this species does not vary across the transect length.

<u>Occurrence analysis:</u>

The preliminary analysis of potentially confounding variables performed before the modelling process proved that none of these variables had a significant impact on the sampling process, with the resulting p-values being always > 0,05 (Appendix - Supplementary table 2).

After demonstrating that these variables had no impact in the sampling process, we conducted the model selection procedure to identify the more influential predictor(s) shaping the occurrence of *D. sargus.* As evidenced in table 9, the model that included 'Rugosity' as the explanatory variable presented the lowest BIC value among all candidate models, inclusively the null model (69.661). The inclusion of a second predictor led to higher BIC values, meaning that the model with 'Rugosity' as a single predictor was more efficient in modelling the occurrence of *D. sargus*.

Table 9 - Model selection procedure suggesting that Rugosity had the most explanatory value for the occurrence of *Diplodus sargus* (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion).

Variable 1	**Variable 2**	**AIC**	**BIC**
Tide	-	67,054	70,796
Moon	-	69,705	73,448
Sunlight	-	62,342	67,955
Wind direction	-	63,472	74,700
Substrate	-	64,470	70,084
Rugosity	-	59,851	**65,464**
Rugosity	Tide	61,629	69,114
Rugosity	Moon	61,850	69,335
Rugosity	Sunlight	59,706	69,062
Rugosity	Wind direction	58,593	73,562
Rugosity	Substrate	62,626	71,982

The final model was deemed to be significantly different from the null model, according to the Vuong Tests results (p-value = 0,012), and its output suggested that *D. sargus* abundance tended to be greater in more complex substrates (levels 2 and 3 of rugosity) (Appendix - Supplementary table 3) However, model diagnostics showed that the model did not perform so well (Appendix – Supplementary figure 16b).

Zebra seabream (*Diplodus cervinus*)

Even though visual inspections of the distribution of seabass abundance across environmental variables suggested that most variables had influence on zebra seabream abundance, there's a high chance that this has to do with the lack of data.

Additionally, the influence analysis of continuous variables with the abundance of *D. cervinus* do not, unequivocally, indicate a tendency or influence of any of the considered continuous variables.

<u>Abundance analysis:</u>

The preliminary analysis of potentially confounding variables indicates that there was no effect by any of the analyzed variables. As evidenced in Appendix - Supplementary table 2, the p-values associated with these variables are all above the 0,05 threshold and therefore they will not be considered.

The model selection results (table 10) point towards a single explanatory variable model. The lowest BIC value was the one referring to the model that used 'Moon' as a predictor, yet the BIC value was higher than the one associated with the null model (67,424).

Table 10 - Model selection procedure suggesting that Moon had the most explanatory value for the abundance of *Diplodus cervinus* (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion).

Variable 1	**AIC**	**BIC**
Tide	66,520	70,221
Moon	65,382	**69,082**
Sunlight	68,431	73,982
Wind direction	67,902	73,452
Substrate	67,219	72,770
Rugosity	67,187	72,738

Additionally, the model with 'Moon' was not deemed to be different from the null, by the comparative Vuong Test. Therefore, it was dismissed, and the null model was considered to be final (Appendix - Supplementary table 3). Accordingly, the complementary Kruskal-Wallis also was not able to indicate any influence of one the analyzed variables on the abundance of *Diplodus cervinus.*

The impact of depth and distance to shore was assessed and the results indicated an influence between distance to shore and the abundance of *Diplodus cervinus*, as evidenced by a p-value of 0,006. As for depth, the results indicate that there was no relation (Appendix - Supplementary table 4).

The plot indicated that the model fit was reasonably good (Appendix – Supplementary figure 23a), denoting a positive effect on species abundance further than 800m from shore. However, it should be noted that the model was resolved with only one effective degree of freedom, resulting in overlapping confidence intervals. Although the p-value suggests the existence of a relation between abundance and the distance, the diagnostic plot (Appendix – Supplementary figure 23b) evidenced a poor performance of the model, with no diagonal tendency in the middle section of the graph. This expected diagonality as to do with the correspondence between the sampled results (y-axis) and the theoretical values (x-axis). If they were similar, the imaginary line created by the points would resemble a positive diagonal, with the values for x' being equal to the results presented in y'.

The GAM to test the effect of depth on the abundance of *Diplodus cervinus* resulted in a p-value > 0,05, meaning that there is no apparent relation between the two variables.

Upon examining the impact of distance from shore along the transect points, we found no significant effect on the abundance of *Diplodus cervinus* (Appendix - Supplementary table 5), as evidenced by p-values > 0,05.

<u>Occurrence analysis:</u>

The preliminary analysis of potentially confounding variables showed that none of the analyzed variables exhibited an effect on *D. cervinus* abundance (Appendix - Supplementary table 2). The p-values of this test suggested that none had a significant impact, since all are above the 0,05 threshold.

The model selection process was completed, and the model featuring 'Tide' as the only explanatory variable exhibited the lowest BIC value (table 11). Moreover, this model had a lower BIC value than the null model (52,504).

Table 11 - Model selection procedure suggesting that Tide had the most explanatory value for the occurrence of *Diplodus cervinus* (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion).

Variable 1	**AIC**	**BIC**
Tide	51,514	**55,215**
Moon	52,029	55,730
Sunlight	54,186	59,736
Wind direction	53,341	58,891
Substrate	52,635	58,185
Rugosity	54,129	59,679

Even though the suggested model had a lower BIC value than the null model, the Vuong test indicated that they were not significantly different (p value = 0,442). Therefore, the null model was determined to be final (Appendix - Supplementary table 3).

Black seabream (*Spondyliosoma cantharus*)

The results of this descriptive analysis were skewed due to the lack of data. There are few trends to be pointed out, such as a tendency for higher abundance in mixed substrates.

Abundance Analysis:

The test performed before the modelling process proved that none of the potentially confounding variables had a significant impact on the sampling process of the species, as p-values were always > 0,05 (Appendix - Supplementary table 2).

The model selection process was performed, and the model with 'Tide' as the sole explanatory variable showed the lowest BIC value. Introducing a second predictor did not enhance the model's performance (table 12). Moreover, this model had a lower BIC value compared to the null model (55,244).

Table 12 - Model selection procedure suggesting that Tide had the most explanatory value for the abundance of *Spondyliosoma cantharus* (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion).

Variable 1	**AIC**	**BIC**
Tide	49,864	**53,606**
Moon	55,372	59,115
Sunlight	52,907	58,520
Wind Direction	55,182	64,538
Substrate	55,622	61,236
Rugosity	56,501	62,114

However, the Vuong test indicated that the model using 'Tide' as a predictor was not significantly different from the null model (p = 0,050). As so, no predictors were included in the final model (Appendix - Supplementary table 3). Yet, the complementary Kruskal-Wallis indicated an influence of 'Tide' on the abundance of *Diplodus cervinus* (χ^2 = 5,724, Df = 1, p-value = 0,016).

The outputs of GAMs to test the influence of depth and distance to shore on black seabream abundance indicated that none of these variables had a significant effect on species abundance (Appendix - Supplementary table 4).

Upon examining the impact of distance from shore along the transect points, we found no significant effect on the abundance of *Spondyliosoma cantharus* (Appendix - Supplementary table 5), as evidenced by p-values > 0.05.

Occurrence analysis:

The test performed to evaluate a possible interference of the three potentially confounding variables showed that none of these variables had an effect on the occurrence of this species, thus they were not included in the modelling process (Appendix - Supplementary table 2).

The model selecting procedure selected 'Tide' as the most relevant variable (table 13), with the inclusion of a second predictor not improving the BIC value. The final model including 'Tide' as a single explanatory variable had a better BIC value than the null model (BIC = 55,244).

Table 13 - Model selection procedure suggesting that Tide had the most explanatory value for the occurrence of *Spondyliosoma cantharus* (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion).

Variable 1	**Variable 2**	**AIC**	**BIC**
Tide	-	46,412	**50,155**
Moon	-	53,127	56,869
Sunlight	-	49,987	55,600
Wind direction	-	51,953	61,309
Substrate	-	53,152	58,765
Rugosity	-	54,064	59,678
Tide	Moon	48,305	53,919
Tide	Sunlight	45,182	52,667
Tide	Wind direction	47,650	58,877
Tide	Substrate	49,373	56,858
Tide	Rugosity	50,408	57,893

The Vuong Test indicated that these models were significantly different (p = 0,027), sustaining that the model with 'Tide' was the most fitted one among all candidate models. The occurrence of black seabream tended be significantly more frequent during ebb tides compared to flood tides (Appendix - Supplementary table 3). However, model diagnostics showed that the model did not perform so well (Appendix – Supplementary figure 18b).

Common Octopus (*Octopus vulgaris*)

This species seems to prefer harder substrates (no sightings in soft substrate) and a tendency for preferring more rugose substrates in detriment of smoother ones (Appendix – Supplementary figure 7f). Also, a greater abundance of *Octopus vulgaris* occurred during ebb tides since only one sighting happened during the flood tide (Appendix – Supplementary figure 7a).

The initial analysis of the relation between abundance and the continuous variables reveal that the species' sightings only occurred up until 30 meters of depth (Appendix – Supplementary figure 13d). Not one individual was spotted in deeper areas.

<u>Abundance Analysis:</u>

The preliminary analysis of potentially confounding variables indicated that none of the possibly interfering variables had a considerable impact in the sampling process (Appendix - Supplementary table 2). Therefore, we proceeded to the modelling process without considering any 'weight' variable.

The BIC values show that the model with 'Tide' as a single explanatory variable presented the most reliable scenario, since it had the lowest BIC among all the candidate models (table 14), including the null model (56,630).

Table 14 - Model selection procedure suggesting that Tide had the most explanatory value for the abundance of *Octopus vulgaris* (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion).

Variable 1	**Variable 2**	**AIC**	**BIC**
Tide	-	51,250	**54,993**
Moon	-	52,904	56,646
Sunlight	-	56,865	62,479
Wind direction	-	57,302	62,916
Substrate	-	55,910	61,523
Rugosity	-	54,059	59,672
Tide	Moon	50,336	55,950
Tide	Sunlight	54,130	61,615
Tide	Wind direction	54,231	61,716
Tide	Substrate	51,944	59,429
Tide	Rugosity	52,804	60,289

The Vuong test indicated that the final model and the null model were significantly different ($p = 0,042$). The model output indicated that the abundance of octopus tended to increase during ebb tides, but this effect turned out to be statistically non-significant (p-value > 0,05). Thus, only the null model could be considered (Appendix - Supplementary table 3).

However, the complementary Kruska-Wallis pointed out 'Tide' as a significantly influential variable. ($\chi^2 = 4,742$, Df = 1, p-value = 0,029).

The impact of depth and distance to shore on the abundance of *Octopus vulgaris* (Appendix - Supplementary table 4) indicated no significant relation between either depth or distance to shore and the abundance of *Octopus vulgaris*, as evidenced by the p-values of 0.242 and 0.469, respectively, both of which are above the 0.05 threshold.

Analysis of the effect of distance to shore along the transect points suggested no significant relation with the abundance of *Octopus vulgaris*. The p-values associated with the comparison between the first reference point (50 m from shore) with the remaining points (150 m and 250 m from shore) were all greater than 0.05 (Appendix - Supplementary table 5).

Occurrence analysis:

The tests suggests that none of the potentially confounding variables had an influence on the sampling process (Appendix - Supplementary table 2), hence they were not considered in the modelling process.

The BIC values indicated that the model using 'Tide' as the sole explanatory variable was the most reliable, as it had the lowest BIC among all the different models (table 15). This model had a lower BIC value than the null model's (48,598).

Table 15 - Model selection procedure suggesting that Tide had the most explanatory value for the occurrence of *Octopus vulgaris* (AIC - Akaike Information Criterion, BIC = Bayesian Information Criterion).

Variable 1	**Variable 2**	**AIC**	**BIC**
Tide	-	51,250	**54,993**
Moon	-	52,904	56,646
Sunlight	-	56,865	62,479
Wind direction	-	57,302	62,916
Substrate	-	55,910	61,523
Rugosity	-	54,059	59,672
Tide	Moon	50,336	55,950
Tide	Sunlight	54,130	61,615
Tide	Wind direction	54,231	61,716
Tide	Substrate	51,944	59,429
Tide	Rugosity	52,804	60,289

The Vuong test showed they were significantly different, with a p-value of 0.043, which is below the 0.05 threshold. However, the effect of Tide turned out to be nonsignificant ($p = 0,054$). Therefore, the influence of this variable was not considered, and the null model was deemed final (Appendix - Supplementary table 3).

Discussion

A thorough analysis of the sampling procedure used in this study is required to decipher if this is a viable method for assessing the distribution and abundance of commercially relevant species and sustaining its use by future applications that may rely on this sampling and analytical framework. Compared to other monitoring techniques, BRUVs have some issues. BRUVs are designed to attract mostly carnivorous fish, yet this should not pose an obstacle within the scope of this study because most fish species with commercial value in Portugal are partially or fully carnivorous. Also, as a video dependent technique, the environmental conditions are a major factor in determining the effectiveness of the sampling process, since increased turbulence or turbidity will affect the quality of the videos and, therefore, the ability to detect and identify fish species in video samples (Frehse et al, 2020). To address this issue, the deployments were planned *a priori* and scheduled based on weather forecasts

Nonetheless, the use of this type of monitoring technique has been growing exponentially due to its benefits compared to other methods. For instance, BRUVs have a really good cost-benefit ratio, since it has proven to be effective besides being relatively unexpensive (Jaco et al, 2020). The most important benefit of using this type of remote mechanisms is that the negative impact that the presence of a diver might have on fish behaviour (e.g., by scaring them away) is precluded with this remote approach (Garcia et al, 2021). Further, compared to catch and release methods, this method is much easier to implement and non-invasive, since environmentally wise, it has little impact by acting only as a fish attractant. Additionally, the fact that it does not require the capture of fish makes it a viable solution for monitoring protected areas, acknowledging that environmental welfare is an obligation within these areas and this method precludes any type of stress while monitoring the biological communities. This preliminary study demonstrates the feasibility of using BRUV sampling techniques in sensitive areas to monitor distribution and abundance of relevant fisheries resources.

Regarding the statistical analysis, a GLM-type modelling process should be preferable over a more simplistic variance analysis or non-parametric rank-based analysis because this type of data often fails to comply with the assumptions of parametric analysis (Cleophas et al, 2011) and traditional rank-based analysis does not provide a robust method to compare the performance of different candidate predictors. The ability to determine the most influential predictor allows researchers to identify the main ecological processes underlying species distribution and abundance. However, the conclusions derived from this approach may require considerable sample sizes to ensure robustness, since a large number of candidate predictors might result in unbalanced samples across the categories of explanatory variables. In this study, some variables turned out to exhibit an unbalanced number of samples across categories due to a relatively low sampling effort, which precluded a more structured sampling of all the candidate variables considered. Potential bias resulting from unbalanced sampling should thus be taken into consideration when interpreting the results of this study and may partially explain the fact that the modelling process was unable to develop more complex models incorporating more than one predictor. For instance, the fact that most deployments took place in shallow waters may have skewed the results and the ability to determine the biological responses to greater water depths.

The most frequent family observed was Sparidae, in accordance with reports by previous studies that made a categorization of this area (Almada, 1996; Vasco-Rodrigues et al, 2011). Additionally, this result is also in conformity to the typical temperate reef fish communities of the north-eastern Atlantic (Bertoncini et al, 2010). Compared to previously published check lists of ichthyofauna in Berlengas (e.g. Vasco-Rodrigues et al, 2011), this study registered 8 new fish species.

Dicentrarchus labrax was the most abundant species, followed by *Diplodus vulgaris* and *Trisopterus luscus*. Other than *Diplodus vulgaris*, the high relative abundance of the other two species is related to the fact that large shoals comprising as much as ~700 individuals were sampled at two occasions. Since these species were infrequently sampled, these shoals produced deviating values which acted as outliers in our database, making the modelling procedure difficult. On the other hand, some species were rarely identified. Species with a relatively high market value such as *Mullus surmuletus* or *Conger conger* were not spotted enough times to be eligible for modelling. The fact that the latter was visualized in seven different deployments demonstrates the utility of this sampling method for monitoring more cryptic fauna. The conger is a nocturnal species which tends to remain motionless inside crevices and holes during the daytime (Xavier et al, 2010). As so, previous studies have been unable to detect it (Almada, 1996 & Vasco-Rodrigues et al, 2011). In the present study, the use of external bait in some BRUV deployments seemingly enabled the detection of this elusive species since it was recorded mostly in BRUV sets equipped with external bait. The attraction of conger towards the BRUV may thus depend on visual stimuli produced by external bait in addition to bait smell.

Likewise, we were able to identify *Epinephelus marginatus*, an endangered species whose extraction from the BNR is forbidden. This shows the utility of this method to monitor the occurrence of protected species around areas of interest. The abundance threshold used in the species selection process resulted in six species being eligible for modelling, but it should be acknowledged that this threshold could have been stricter. Indeed, abundance data with too many zeros are more challenging to be modelled and may bring considerable uncertainty to the modelled responses, thus making the trends less conclusive. Notwithstanding, there are some illations to be taken from the results achieved.

Firstly, the preliminary assessment of potentially confounding variables which could have interfere with the sampling process proved to be useful, since it enabled the incorporation of weighing factors in the model to account for their effects. Only visibility and external bait were judged to have had an impact on the sampling process, and this impact was seemingly contrasting for different species. A greater visibility was associated with higher abundance of *Diplodus vulgaris,* whereas the opposite was verified for *Dicentrarchus labrax*. Explaining the negative influence of poor visibility on the sampling efficacy is straightforward because the video samples require adequate visibility to be processed, and samples with low visibility will have a narrower field of vision and thus will be most prone to bias due to the underestimation of species abundance if individuals move outside the range of visual detection. On the other hand, a positive effect of poor visibility on fish relative abundance, as observed in *D. labrax,* could relate with behavioural traits. De Robertis et al. (2003) indicated that the predatory pressure exerted by piscivorous fish decays in turbid environments. The visibility of objects is much reduced in turbid waters compared to clearer waters, and therefore the foraging behaviour associated with feeding mechanisms may be reduced under these conditions. Some species could thus seek more turbid waters as a refuge from potential predators. Yet, other species could benefit from foraging in more turbid waters to avoid being detected by their prey. *D. labrax*, for instance, is known to forage on the surf zone where visibility is greatly reduced (Rodriguez-Garcia et al, 2024). Notwithstanding, it should be noted that this species was detected in few samples and that the effect of visibility could result from large shoals of *D. labrax* being recorded mostly in low visibility conditions by chance.

Regarding the effect of external bait, *D. sargus* demonstrated to be positively influenced by its presence, similarly to *C. conger*. This might have to do with the fact that, when additional bait was inserted in an external mesh bag, it introduced a new visual stimulus due to its presence and responsiveness to the water currents, which generated movements likely to have attracted these species. *Diplodus sargus* are very visual and responsive to movement of prey (Bowmaker, J.K. & Loew, E.R. 2008), and the external bait provides something to nibble, becoming potentially more attractive.

Topographic features including substrate type and rugosity showed to interact with the abundance of several species. This is in accordance with expected results since the six species analyzed have a tendency to forage in more complex, rocky substrates with formations like crevices, holes and pikes (Sharifian et al., 2023). This preference could relate with many factors including reproductive behaviour, food availability, and protection from predators (Connell & Jones. 1991).

Additionally, the preliminary boxplots suggest an interference of the tidal phase on the abundance and visualization of the *Octopus vulgaris.* However, this suggestion is no corroborated by neither the models nor the complementary Kruskal-Wallis test.

The preliminary tests suggest distance to shore to be influential on *Dicentrarchus labrax*, since most sightings where within 1000 meters from shore. The waters closer to shore tend to be more productive, with more prey availability and composed by more complex habitats when compared to areas further away from shore (Pittman & McAlpine. 2003). However, this influence was not significant enough to be indicated by the GAM analysis.

Also, depth was determined by the descriptive analysis as potentially influential, in this case, for three different species. *Diplodus vulgaris, Diplodus sargus* and *Octopus vulgaris* sightings may have been influenced by depth. The tendency was the same for the three species, with most sightings occurring until the 30 m isobath. On the other hand, the designed models only confirmed this tendency for *Diplodus sargus.*

The models designed to quantify the impact of each of the categorical variables were drafted carefully, following the forward-stepwise mechanism, always aiming for maximum parsimony, a principle that implies choosing the simplest explanatory model possible for similar explanatory powers. Out of the twelve explanatory GLMs created during this process (i.e., one abundance and one occurrence model for each species), the most parsimonious model turned out to be the null model in seven of them (*Dicentrarchus labrax* – occurrence, *Spondyliosoma cantharus* – abundance, *Diplodus vulgaris* – occurrence, *Octopus vulgaris* – abundance and occurrence, *Diplodus cervinus* – abundance and occurrence). These null models are little informative, but they could provide clues for interpreting model outputs. For example, when considering the case of *Spondyliosoma cantharus*, no explanatory variable was deemed significant enough to explain the distribution patterns of the species. However, since a simpler binomial model was able to detect the influence of ‘Tide’ on the occurrence of the same species, one can assume that the non-zero abundance data were not enough to adequately run a count-based model. On the other hand, whenever the null models were chosen in the analysis of species occurrence (*Dicentrarchus labrax* and *Diplodus vulgaris*), this could simply translate into no tendencies being determined because species were equally present across the environmental factors herein considered. Indeed, since the models of abundance identified significant trends in the same species, it would not be plausible that the lack of results for occurrence were derived from a lack of data given the much less data-demanding characteristics of the binomial approach.

The cases where the null model was selected for both abundance and occurrence (i.e., *Octopus vulgaris* and *Diplodus cervinus*) are also thought to have resulted from the lack of data. The somewhat small sample size may have hindered the effectiveness of the modelling process due to a low number of sightings likely insufficient to be related with a predictor. In these cases, the fact that whenever species were sighted only one individual was recorded resulted in abundance data being very similar to occurrence, binomial data.

On the other hand, the remaining five models suggest a significant influence of one of the candidate categorical variables. Tide was selected as the most influential variable in three of these models (*Dicentrarchus labrax* – abundance, *Spondyliosoma cantharus* – occurrence, *Diplodus vulgaris* – abundance). A positive influence of ebb tides on species abundance or occurrence was detected, which could relate to increased foraging activity during this tidal phase (Rountree & Able. 1992; Couto et al, 2022).

The modelling of *Diplodus sargus* rendered the best results due to its comparatively greater abundance. For both abundance and occurrence, 'Rugosity' was deemed to be the most appropriate explanatory variable, with a positive influence associated with higher levels of substrate complexity. The geological formations on the substrate create hiding spots for juveniles and adults, whilst still being more prolific in abundance of prey. (García-Charton & Pérez-Ruzafa 2001; Sharifian et al., 2023)

The GLM outputs to examine the variation in species abundance between transect points revealed significant effects for *Diplodus vulgaris* only, likely because it was the most abundant species. A higher abundance of *D. vulgaris* seems to occur at 150 m from shore compared to closer (50 m) and further (250 m) distances from shore. This could imply that the 50-m fishing restriction limit (*Diário da República, 1ª série — Nr. 228 — 24 de Novembro de 2008)* is not effective for this species and that there are areas which would be more productive to protect. However, *Diplodus vulgaris* is a low-value species and, as shown by the results, its abundance demands little concerns. Therefore, the social and economic costs of a possible change on the legislation would overcome the potentially positive impact that such an alteration could have. Given that the modelling process was not so effective, it would be reasonable to suggest a greater sampling effort to augment the available data and determine if the abundance of other species around the island exhibit any spatial trends. Such knowledge would clarify managers about the distribution pattern of marine resources in this protected area and guide management-enhancing strategies to the MPA of Berlenga.

The aim of quantifying the effect of variables on the abundance of species also extended to two continuous variables: depth and distance from shore. GAMs were performed in order to assess the impact of these variables and the results showed that the abundance of *Diplodus sargus* was negatively influenced by depth, with a positive impact of the variable up until 24 meters and a negative impact from this point onwards, which is in accordance with (Sala & Ballesteros, 1997) information, that states that this species can go to depths up to 150 m but tends to stay within the first 30 m. Additionally, GAMs indicated a positive influence of distance from shore on the abundance of *Diplodus cervinus* at distances > 800 m. Even though this is a common behaviour on some species (Sharifian et al., 2023), that due to their migratory patterns or feeding habits prefer areas further away from shore, there is to our knowledge no research describing this pattern in this species. Despite this tendency, this trend could not be associated with the transect analysis due to a much larger spatial scale.

In this study, 8 species of commercially relevant fish fauna were identified. This result sustains that BRUV can be an effective instrument to sample fisheries resources non-invasively in protected areas. Remote technics, like the BRUV, have been tested to survey communities in many different habitats, allowing researchers to monitor areas that are harder to reach (greater depths) or to monitor with visual census (colder water temperatures) (Frehse et al, 2020). It also precludes the risk of double counting individuals since the relative abundance of a species is estimated through MaxN (Frehse et al, 2020).

Remote sampling methods offer an extended operational capacity by not relying on human operators. This technique, combined with automated processing of video samples, could endow researchers, managers and stakeholders with a long-term, continuous monitoring system of marine fauna in regions of particular interest, such as MPAs. By taking advantage of current technologies, it would be possible implementing an autonomous video-based monitoring system targeting marine resources in Berlengas, which would render biological and environmental data in real time to be processed with algorithms fuelled with Artificial Intelligence for automatic species identification. This type of tools have been already emerging in the literature (Lade et al., 2023). The timeliness of such information would enable the spatial management of MPA resources in real time, thus contributing to optimize the performance of these conservation units.

This study also provided some information on the distribution and abundance patterns of fisheries resources, pointing substrate type and rugosity as the most influential environmental variables on species habitat selection, sustaining the argument that this monitoring mechanism could provide ecological knowledge and the environmental impact of the different variables on species that would be harder to assess.

The analysis regarding distance to shore was not so prolific as the GAM analysis only indicated an influence of this variable on *Diplodus vulgaris*, possibly due to the shortness of data. The GLM transect analysis suggested that, following a conceptual transect, the abundance of *Diplodus vulgaris* was larger at 150 m from shore comparing to areas closer to shore, implying that the current spatial design for the no-fishing area could be not so effective for this species.

This method’s performance is promising, and further effort is required in order to complement the sampling size, in order to detect patterns in species that are not as abundant or frequent as Diplodus vulgaris. This will provide evidence-based knowledge to optimize the region’s marine spatial planning.

Final considerations

The methodological approach presented in this study provided a relatively low cost and fast solution to combine several sources of data into a meaningful georeferenced guide on priority areas. This study represents a preliminary effort that aimed to assess BRUV ability to monitor fishing resources in the BNR, acknowledging that it could be replicated in other parts of the world.

The results of this project suggest that, for a proper monitoring effort, confounding variables must be taken into consideration. Both visibility and tilt could have an impact on the collected recordings, possibly skewing the results. Additionally, using external bait could imply different results, since species like the conger were attracted to it. Therefore, these factors must be taken into consideration and require further investigation.

Regarding the effect of the different environmental variables, the physical traits of the substrate were determined to have a meaningful impact. The type of substrate and most importantly, its rugosity were deemed to be influential on the abundance and occurrence of different species. Also, the tidal phase was considered to be potentially important since there are evidence pointing towards an impact of this variable on the abundance and occurrence of some species. Accordingly, the models also suggest an influence of depth on *Diplodus sargus*, indicating a negative tendency towards deeper environments.

The determination of the effects of distance from shore warrants a greater sampling effort. GAMs indicated a positive influence of distance from shore on *Diplodus cervinus* abundance, but at short distances from shore no differences were observed. At short distances, only *Diplodus vulgaris* exhibited some significant variability, but since this is an abundant species with low commercial value it alone does not raise any particular concern regarding the MPA spatial design currently operating.

This study was able to provide a baseline to direct future monitoring efforts, deeming BRUV as an effective method to evaluate the state of marine faunal communities and their responses to a ever-changing environment, enabling scientifically informed management decisions. Nonetheless, the underlying data used in this study still has limitations and could be significantly improved with additional sampling effort that would enhance the performance of the analytical framework, enabling more well-supported conclusions.

Appendix

Supplementary table 1 - Deployment details.

Code	Date	Replicate	Transect_(y/n)	Area	Sector	Depth	Sec_to_Bottom	Distance_Shore	Tide	Moon	Surface_Temperature	Sunlight	Visibility	Wind_intensity_(km/h)	Wind_direction	Substrate	Rugosity
BRUV1	16/04/2021	X	N	Cavalete	4	14	45	130	Vazante	Crescente	15,88	2	1	11,2	N	hard	2
BRUV2	01/06/2021	1	N	Caca	1	41	54	900	Vazante	Minguante	16,54	1	2	8,1	W	hard	2
BRUV3	01/06/2021	2	N	Caca	1	38	47	845	Vazante	Minguante	16,54	1	2	8,1	W	hard	3
BRUV4	01/06/2021	3	N	Caca	1	26	38	848	Vazante	Minguante	16,54	1	1	8,1	W	hard	2
BRUV5	01/06/2021	1	N	Broeiro do sol	4	32	55	2058	Enchente	Minguante	16,54	1	1	8,1	W	hard	3
BRUV6	01/06/2021	2	N	Broeiro do sol	4	51	53	2088	Enchente	Minguante	16,54	1	2	8,1	W	mixed	1
BRUV7	01/06/2021	3	N	Broeiro do sol	4	22	36	2120	Enchente	Minguante	16,54	1	2	8,1	W	hard	2
BRUV8	05/07/2021	1	N	O-da-Velha	1	24	53	510	Enchente	Minguante	16,61	1	2	6,7	W	hard	3
BRUV9	05/07/2021	2	N	O-da-Velha	1	24	46	462	Enchente	Minguante	16,61	1	2	6,7	W	hard	2
BRUV10	05/07/2021	3	N	O-da-Velha	1	26	59	546	Enchente	Minguante	16,61	1	1	6,7	W	hard	2
BRUV11	05/07/2021	1	Y	Baixa do Guindaste	2	29	53	558	Vazante	Minguante	16,61	1	1	8,5	W	hard	1
BRUV12	05/07/2021	2	Y	Baixa do Guindaste	2	18	37	427	Vazante	Minguante	16,61	1	1	8,5	W	hard	2
BRUV13	05/07/2021	3	Y	Baixa do Guindaste	2	27	38	471	Vazante	Minguante	16,61	1	1	8,5	W	hard	2
BRUV14	16/07/2021	1	N	Atafana da terra	3	27	71	1165	Vazante	Crescente	16,61	3	2	1,6	N	hard	3
BRUV15	16/07/2021	2	N	Atafana da terra	3	20	59	1172	Vazante	Crescente	16,61	3	2	1,6	N	hard	3
BRUV16	16/07/2021	3	N	Atafana da terra	3	19	56	1117	Vazante	Crescente	16,61	3	1	1,6	N	hard	2
BRUV17	16/07/2021	1	Y	Baixa dos pregos	4	16	61	107	Vazante	Crescente	16,61	3	2	1,6	N	hard	3
BRUV18	16/07/2021	2	Y	Baixa dos pregos	4	23	53	119	Vazante	Crescente	16,61	3	2	1,6	N	mixed	2
BRUV19	16/07/2021	3	Y	Baixa dos pregos	4	22	61	321	Vazante	Crescente	16,61	3	2	1,6	N	hard	2
BRUV20	11/08/2021	1	N	Baixinhas	1	13	58	798	Vazante	Crescente	17,16	1	1	18,3	N	hard	1
BRUV21	11/08/2021	2	N	Baixinhas	1	16	63	847	Vazante	Crescente	17,16	1	2	18,3	N	hard	3
BRUV22	11/08/2021	3	N	Baixinhas	1	17	43	779	Vazante	Crescente	17,16	1	1	18,3	N	hard	2
BRUV23	11/08/2021	1	Y	Entre Ilhao da quebrada e carreiro dos cacoes	1	14	47	122	Enchente	Crescente	17,16	1	1	17,4	N	hard	3
BRUV24	11/08/2021	2	Y	Entre Ilhao da quebrada e carreiro dos cacoes	1	17	51	219	Enchente	Crescente	17,16	1	2	17,4	N	hard	2
BRUV25	11/08/2021	3	Y	Entre Ilhao da quebrada e carreiro dos cacoes	1	18	61	323	Enchente	Crescente	17,16	1	1	17,4	N	hard	2
BRUV26	30/08/2021	1	N	Baixa do Broeiro	4	13	71	2198	Vazante	Minguante	18,86	3	1	2,7	E	hard	2
BRUV27	30/08/2021	2	N	Baixa do Broeiro	4	20	57	2004	Vazante	Minguante	18,86	3	2	2,7	E	hard	3
BRUV28	30/08/2021	3	N	Baixa do Broeiro	4	20	58	2170	Vazante	Minguante	18,86	3	1	2,7	E	hard	3
BRUV29	30/08/2021	1	Y	Medas	4	18	33	1543	Vazante	Minguante	18,86	3	1	2,7	W	hard	2
BRUV30	30/08/2021	2	Y	Medas	4	17	43	1443	Vazante	Minguante	18,86	3	2	2,7	W	hard	2
BRUV31	30/08/2021	3	Y	Medas	4	17	47	1342	Vazante	Minguante	18,86	3	1	2,7	W	hard	2
BRUV32	14/10/2021	1	Y	Baixa do iate	3	17	68	46	Enchente	Crescente	18,39	3	2	4,5	E	mixed	2
BRUV33	14/10/2021	2	Y	Baixa do iate	3	16	60	142	Enchente	Crescente	18,39	3	2	4,5	E	hard	3
BRUV34	14/10/2021	3	Y	Baixa do iate	3	21	127	245	Enchente	Crescente	18,39	3	2	4,5	E	hard	3
BRUV35	14/10/2021	1	N	Baixa das Atafonas	3	27	54	1197	Vazante	Crescente	18,39	2	1	4,5	E	hard	2
BRUV36	14/10/2021	2	N	Baixa das Atafonas	3	22	32	1109	Vazante	Crescente	18,39	2	2	4,5	E	hard	3
BRUV37	14/10/2021	3	N	Baixa das Atafonas	3	24	42	1106	Vazante	Crescente	18,39	2	1	4,5	E	hard	3
BRUV38	07/04/2022	1	N	Caca	1	42	94	925	Vazante	Crescente	14,07	1	1	10,1	NW	hard	3
BRUV39	07/04/2022	2	N	Caca	1	38	40	838	Vazante	Crescente	14,07	1	2	10,1	NW	hard	2
BRUV40	07/04/2022	3	N	Caca	1	24	30	850	Vazante	Crescente	14,07	1	1	10,1	NW	hard	3
BRUV41	07/04/2022	1	Y	Baixa da Corredora	2	13	26	74	Enchente	Crescente	14,07	1	1	8,5	W	soft	1
BRUV42	07/04/2022	2	Y	Baixa da Corredora	2	20	28	174	Enchente	Crescente	14,07	1	1	8,5	W	soft	1
BRUV43	07/04/2022	3	Y	Baixa da Corredora	2	24	35	286	Enchente	Crescente	14,07	1	1	8,5	W	mixed	1
BRUV44	27/05/2022	1	N	Vapor do Trigo	2	28	30	733	Enchente	Minguante	16,77	2	2	9,4	SE	hard	1
BRUV45	27/05/2022	2	N	Vapor do Trigo	2	26	33	778	Enchente	Minguante	16,77	2	2	9,4	SE	hard	1
BRUV46	27/05/2022	3	N	Vapor do Trigo	2	24	94	714	Enchente	Minguante	16,77	2	1	9,4	SE	hard	3
BRUV47	27/05/2022	1	Y	Figueiras	2	14	41	94	Enchente	Minguante	16,77	2	1	10,1	NW	hard	3
BRUV48	27/05/2022	2	Y	Figueiras	2	26	36	200	Enchente	Minguante	16,77	2	2	10,1	NW	soft	1
BRUV49	27/05/2022	3	Y	Figueiras	2	28	37	308	Enchente	Minguante	16,77	2	2	10,1	NW	soft	1

Supplementary table 2 - Potentially confounding variables analysis for each species. (Estimate effect, Standard error, Df = Degrees of freedom, Z statistic value, statistical p-value)

Species	**Measure**	**Variable**	**Estimate**	**Std. Error**	**Df**	**z-value**	**p-value**
Dicentrarchus labrax	Abundance	Tilt	19,300	5442,46	42	0,004	0,997
		Visibility	3,560	1,442	45	-2,437	0,013
		Exterior Bait	-6,024	1,772	45	-3,362	0,001
	Occurrence	Tilt	16,060	2284,10	42	0,007	0,994
		Visibility	0,274	0,743	45	-0,369	0,712
		Exterior Bait	-1,609	1,105	45	-1,449	0,147
Diplodus vulgaris	Abundance	Tilt	0,428	0,682	43	0,627	0,530
		Visibility	-0,866	0,298	46	-2,905	0,004
		Exterior Bait	-0,082	0,336	46	-0,244	0,807
	Occurrence	Tilt	-1,652e+01	6,209e+03	43	-0,003	0,998
		Visibility	9,277e-16	1,044	46	0,000	1,000
		Exterior Bait	0,439	1,198	46	0,367	0,714
Diplodus sargus	Abundance	Tilt	17,300	2002,17	43	0,009	0,993
		Visibility	-0,260	0,256	46	-1,013	0,311
		Exterior Bait	0,564	0,254	46	2,216	0,026
	Occurrence	Tilt	17,570	2284,10	43	0,994	0,994
		Visibility	-0,510	0,586	46	-0,870	0,384
		Exterior Bait	1,223	0,677	46	1,807	0,070
Diplodus cervinus	Abundance	Tilt	-0.154	1,080	42	-0,143	0,887
		Visibility	0,196	0,556	45	0,354	0,724
		Exterior Bait	-0,053	0,600	45	-0,089	0,929
	Occurrence	Tilt	-0,470	1,328	42	-0,354	0,723
		Visibility	0,054	0,712	45	0,076	0,940
		Exterior Bait	-0,113	0,774	45	-0,146	0,884
Spondyliosoma cantharus	Abundance	Tilt	-1,299	0,866	43	-1,500	0,134
		Visibility	0,406	0,646	46	0,628	0,530
		Exterior Bait	0,693	0,632	46	1,096	0,273
	Occurrence	Tilt	-2,197	1,344	43	-1,635	0,102
		Visibility	0,510	0,722	46	0,707	0,480
		Exterior Bait	0,898	0,726	46	1,236	0,216
Octopus vulgaris	Abundance	Tilt	1.682e+01	3,301e+03	43	0,005	0,996
		Visibility	-0,847	0,690	46	-1,228	0,220
		Exterior Bait	0,287	0,646	46	0,446	0,656
	Occurrence	Tilt	1.706e+01	3,766e+03	43	0,005	0,996
		Visibility	-0,847	0,776	46	-1,091	0,220
		Exterior Bait	0,287	0,755	46	0,778	0,656

Supplementary table 3 - Final model's results for each species. (Estimate effect, 2,5% and 97,5% confidence interval, Standard Error, Z statistic value, p-value)

Species	Measure	Comparison	Estimate	2,5%	97,5%	Std. Error	z-value	p-value
Dicentrarchus labrax	Abundance	Intercept	0,333	0,040	2,781	1,082	-1,015	0,310
		Tide (Ebb)	94,730	5,910	1518,446	1,416	3,215	0,001
	Occurrence	Intercept	0,230	0,104	0,454	0,370	-3,965	7,33e-05
Diplodus vulgaris	Abundance	Intercept	3,0988	1,972	5,026	0,238	4,759	1,95e-06
		Tide (Ebb)	2,054	1,126	3,718	0,304	2,370	0,018
	Occurrence	Intercept	11,000	4,642	36,537	0,522	4,592	4,40e-06
Diplodus sargus	Abundance	Intercept	0,178	0,030	0,557	0,711	-2,423	0,015
		Ext. Bait (Y)	1,600	0,956	2,659	0,260	1,809	0,070
		Rugosity (2)	6,615	1,980	41,076	0,734	2,574	0,010
		Rugosity (3)	8,000	2,416	49,484	0,730	2,846	0,004
	Occurrence	Intercept	0,111	0,006	0,591	1,054	-2,085	0,037
		Rugosity (2)	21,000	3,001	434,612	1,161	2,621	0,008
		Rugosity (3)	18,000	2,534	374,478	1,167	2,478	0,013
Diplodus cervinus	Abundance	Intercept	0,276	0,152	0,455	0,277	-4,634	3,59e-06
	Occurrence	Intercept	0,270	0,127	0,522	0,356	-3,671	2,42e-04
Spondyliosoma cantharus	Abundance	Intercept	0,208	0,104	0,365	0,316	-4,960	7,03e-07
	Occurrence	Intercept	0,050	0,002	0,240	1,025	-2,924	0,003
		Tide (Ebb)	10,000	1,642	193,612	1,103	2,088	0,036
Octopus vulgaris	Abundance	Intercept	0,208	0,104	0,365	0,316	-4,960	7,03e-07
	Occurrence	Intercept	0,230	0,104	0,454	0,369	-3,965	7,33e-07

Note – These results refer to the comparison of the first factor of the variable with the one enounced.

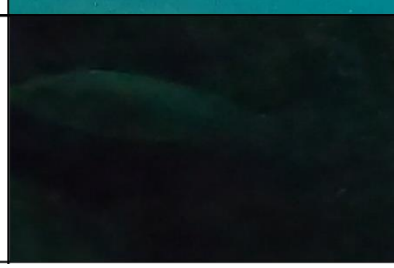
Supplementary table 4 - GAM Results for each species. (Df = Degrees of Freedom, Reference Df, χ^2 = Chi-squared test, Statistical p-value, R^2 = R-squared value, Explained Deviance)

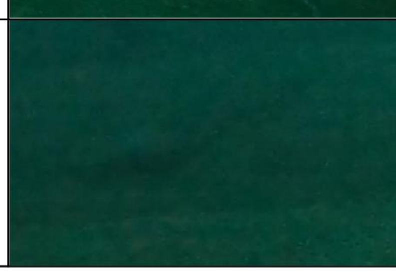
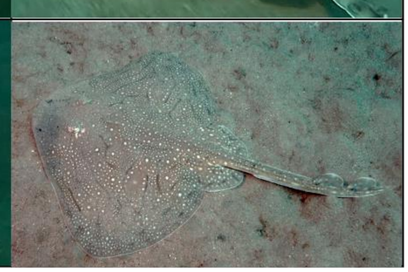
Species	Variable	Df	Ref. Df	χ^2	p-value	R^2	Exp. Dev
Dicentrarchus labrax	Depth	1,274	1,498	0,044	0,932	-0,023	0,015
	Distance	1	1	2,935	0,086	-0,991	0,025
Diplodus vulgaris	Depth	1,912	2,392	1,268	0,696	-0,017	0,044
	Distance	1,758	2,145	4,394	0,107	0,0401	0,112
Diplodus sargus	Depth	1	1	7,299	**0,010**	0,084	0,104
	Distance	1	1	0,760	0,383	-0,023	0,014
Diplodus cervinus	Depth	1	1	2,471	0,116	0,026	0,074
	Distance	1	1	7,291	**0,006**	0,172	0,171
Spondyliosoma cantharus	Depth	1	1	2,588	0,114	0,038	0,072
	Distance	1,843	2,260	2,076	0,424	0,033	0,092
Octopus vulgaris	Depth	1	1	1,403	0,242	-1,960e-04	0,050
	Distance	2,853	3,540	0,983	0,469	3,54	0,051

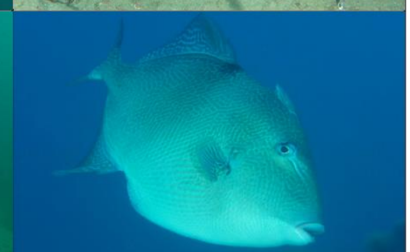
Supplementary table 5 - Transect analysis results for each species. (Estimate effect, 2,5% and 97,5% confidence interval, Standard Error, Z statistic value, Statistical p-value)

Species	Comparison	Estimate	2,5%	97,5%	Std. Error	z-value	p-value
Dicentrarchus labrax	Intercept	0,714	0,108	18,033	1,158	-0,291	0,771
	Replicate (2)	2,000	0,052	76,734	1,606	0,431	0,666
	Replicate (3)	0,200	0,003	10,222	1,866	-0,863	0,388
Diplodus vulgaris	Intercept	2,556	1,138	2,194	0,424	2,216	0,026
	Replicate (2)	**4,402**	1,546	3,726	0,526	2,818	**0,004**
	Replicate (3)	0,860	0,266	4,118	0,592	-0,253	0,800
Diplodus sargus	Intercept	1,000	0,398	2,194	0,428	0,000	1,000
	Replicate (2)	1,142	0,357	3,726	0,590	0,226	0,821
	Replicate (3)	1,286	0,414	4,118	0,578	0,434	0,664
Diplodus cervinus	Intercept	-1,252	-2,348	0,933	0,718	-1,745	0,809
	Replicate (2)	0,405	0,067	1,109	0,929	0,436	0,662
	Replicate (3)	-19,050	-25,998	-2,346	5874,272	-0,003	0,997
Spondyliosoma cantharus	Intercept	-1,252	-2,521	0,143	0,707	-1,772	0,076
	Replicate (2)	-0,693	-1,908	2,641	1,224	-0,556	0,571
	Replicate (3)	-20,050	-39,134	18,982	9685,038	-0,002	0,998
Octopus vulgaris	Intercept	0,286	0,047	0,882	0,707	-1,772	0,076
	Replicate (2)	1,000	0,120	8,332	1,000	0,000	1,000
	Replicate (3)	0,050	0,023	5,218	1,225	-0,556	0,571

Note – These results refer to the comparison of the first factor of the variable with the one enounced, acknowledging that the ‘intercept’ is the comparison of a factor with a mirrored image of itself.

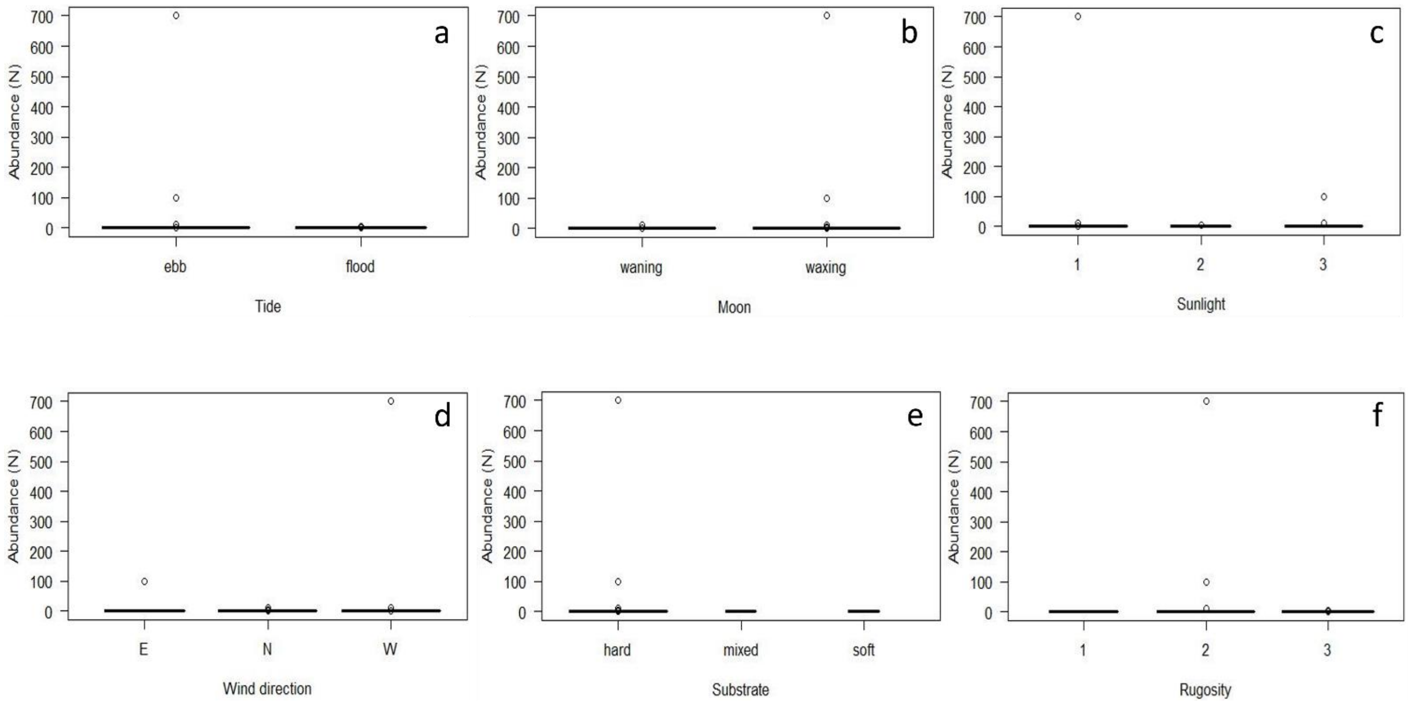
Species	Observed individual	Reference
Diplodus cervinus		
Diplodus sargus		
Diplodus vulgaris		
Pagrus pagrus		
Spondyliosoma cantharus		

Sarda salpa		
Caranx rhonchus		
Pseudocaranx dentex		
Seriola rivoliana		
Raja brachyura		
Raja clavata		
Raja ondulata		

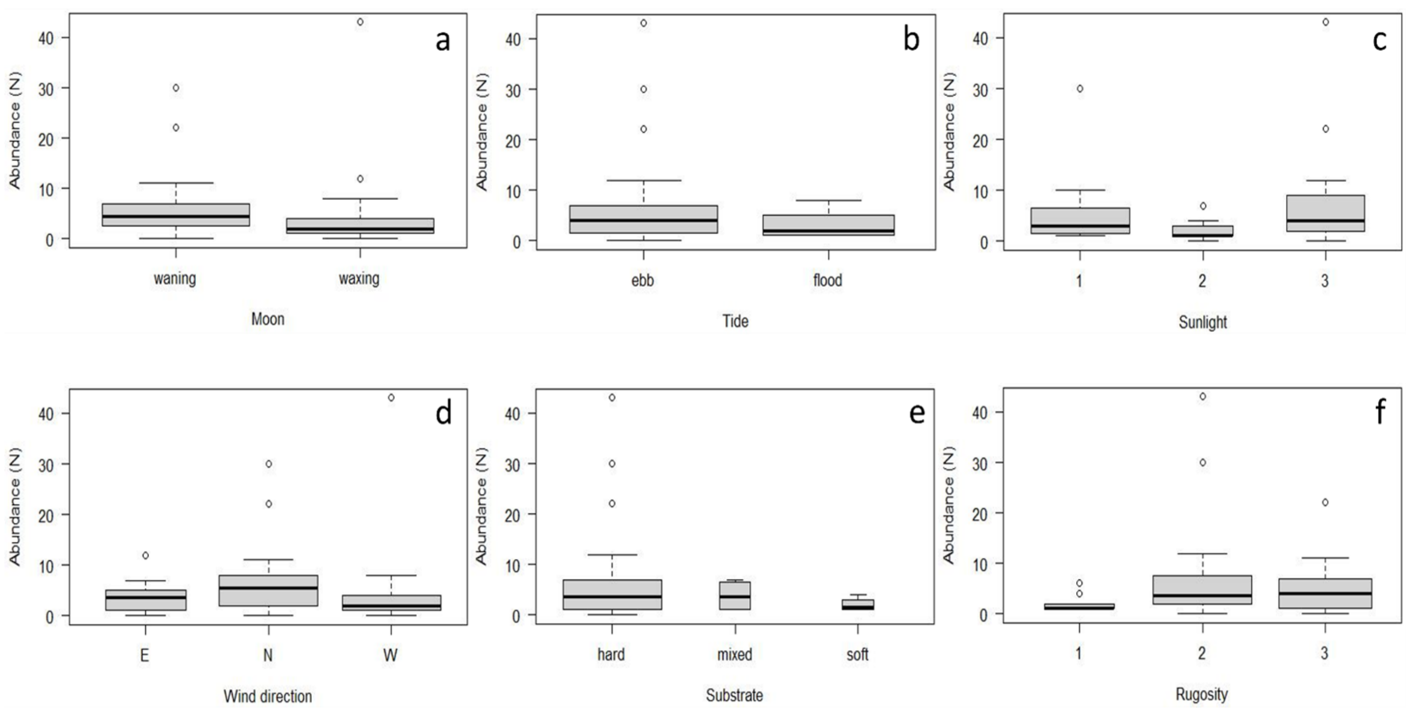
Epinephelus aeneus		
Epinephelus marginatus		
Balistes capriscus		
Conger conger		
Trisopterus luscus		
Dicentrarchus labrax		
Mullus surmuletus		

Muraena helena		
Scyliorhinus canicula		
Chelidonichthys lucerna		
Zeus faber		
Octopus vulgaris		
Loligo vulgaris		
Homarus gammarus		

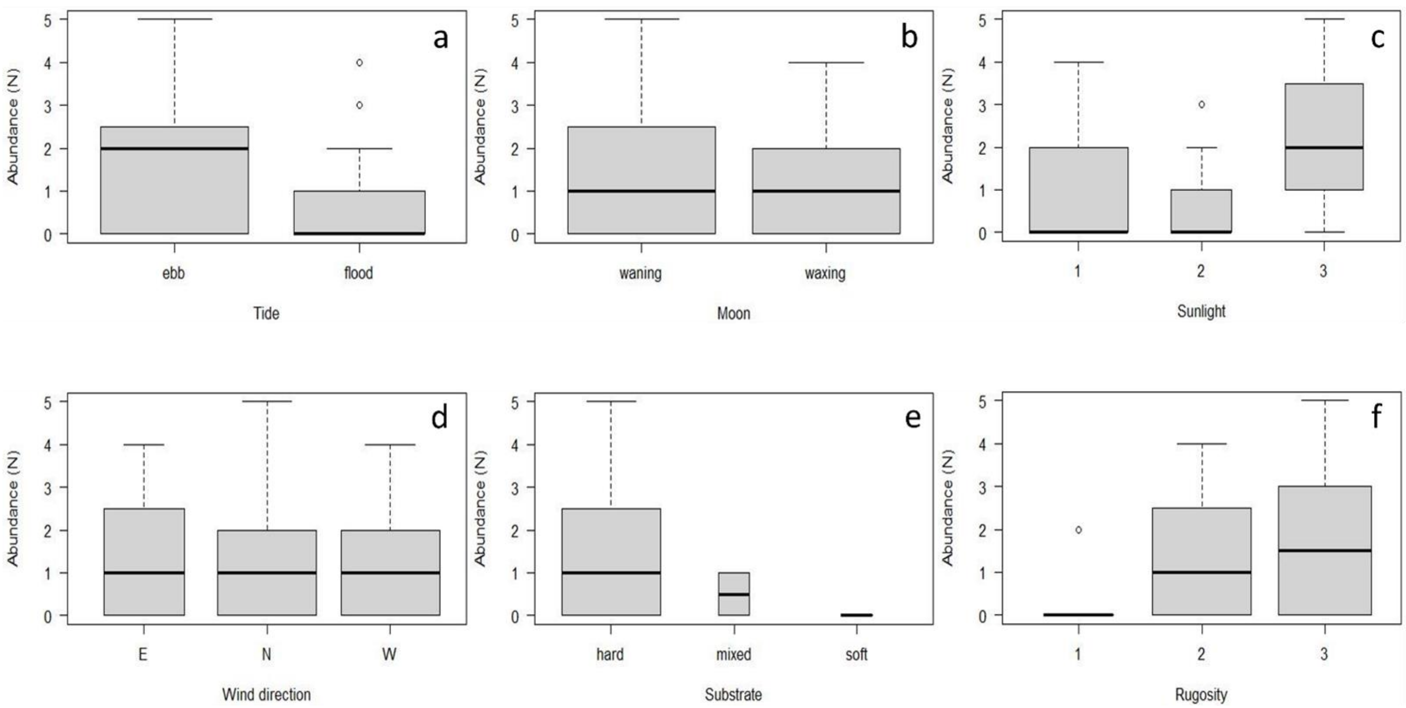
Supplementary figure 1 - Identified species with reference pictures. (Source: iNaturalist & OMARE)



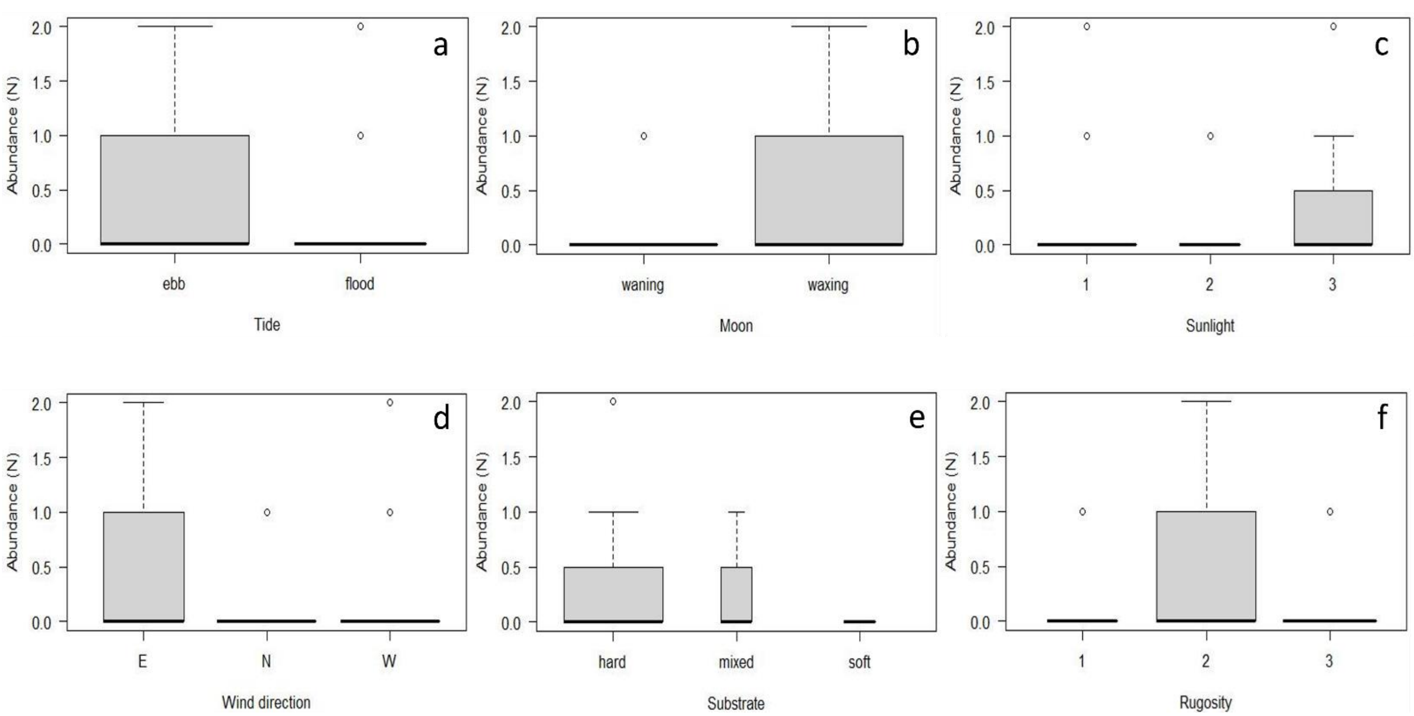
Supplementary figure 2 - Categorical variables analysis for *Dicentrarchus labrax*. (a. Tide; b. Moon; c. Sunlight; d. Wind Direction; e. Substrate; f. Rugosity)



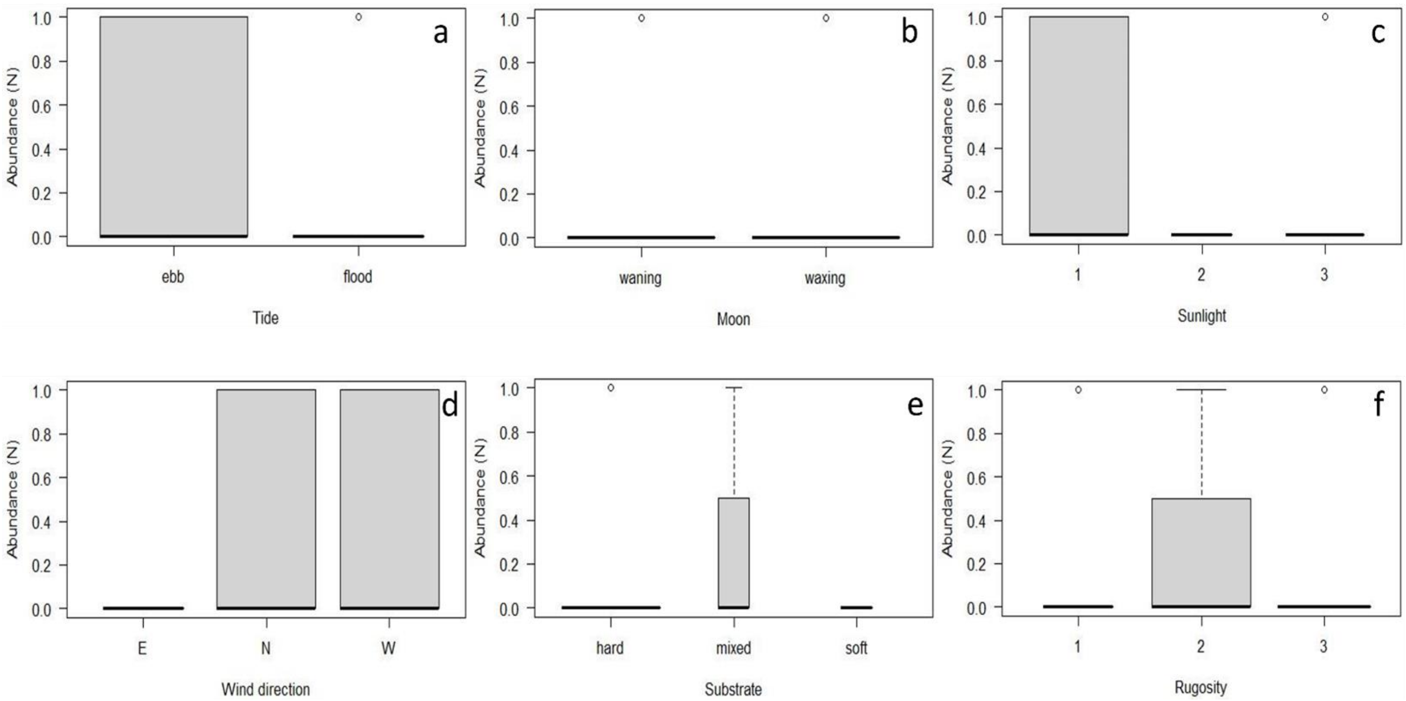
Supplementary figure 3 - Categorical variables analysis for *Diplodus vulgaris.* (a. Tide; b. Moon; c. Sunlight; d. Wind Direction; e. Substrate; f. Rugosity)



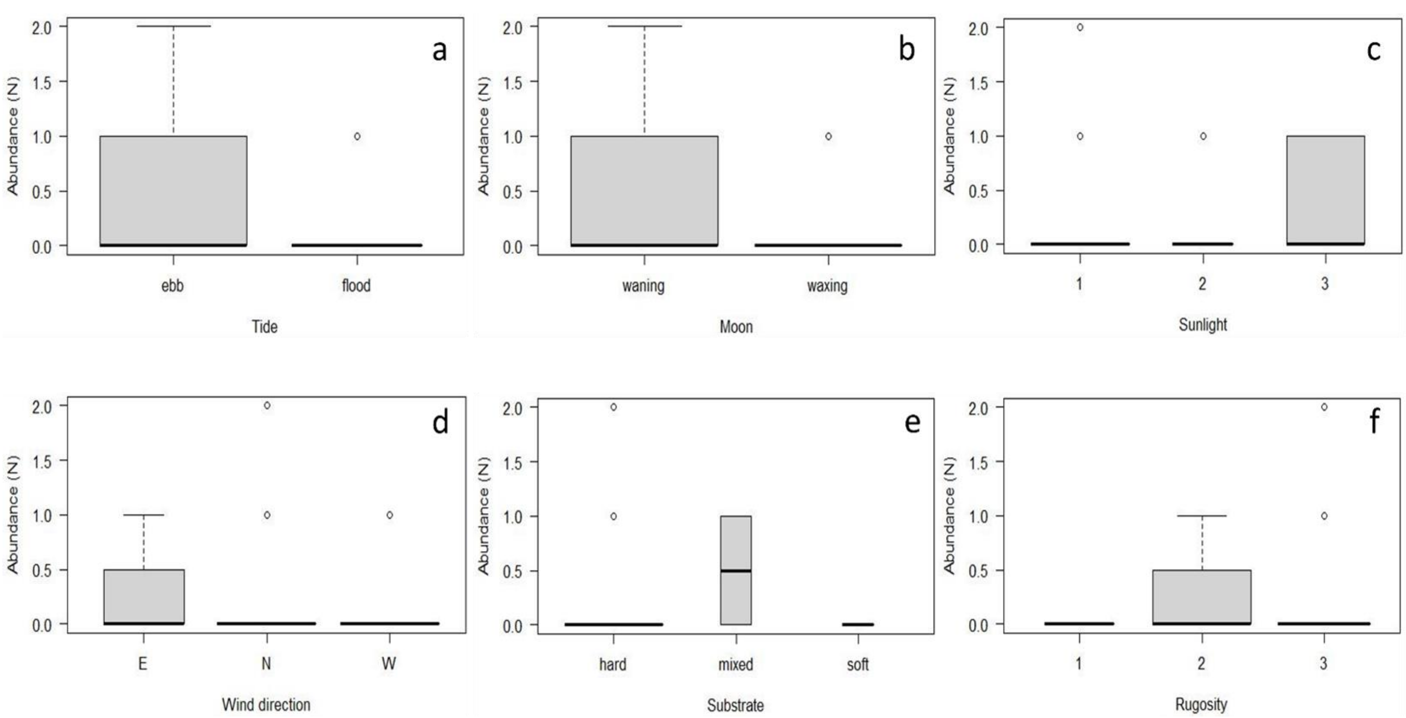
Supplementary figure 4 - Categorical variables analysis for *Diplodus sargus*. (a. Tide; b. Moon; c. Sunlight; d. Wind Direction; e. Substrate; f. Rugosity)



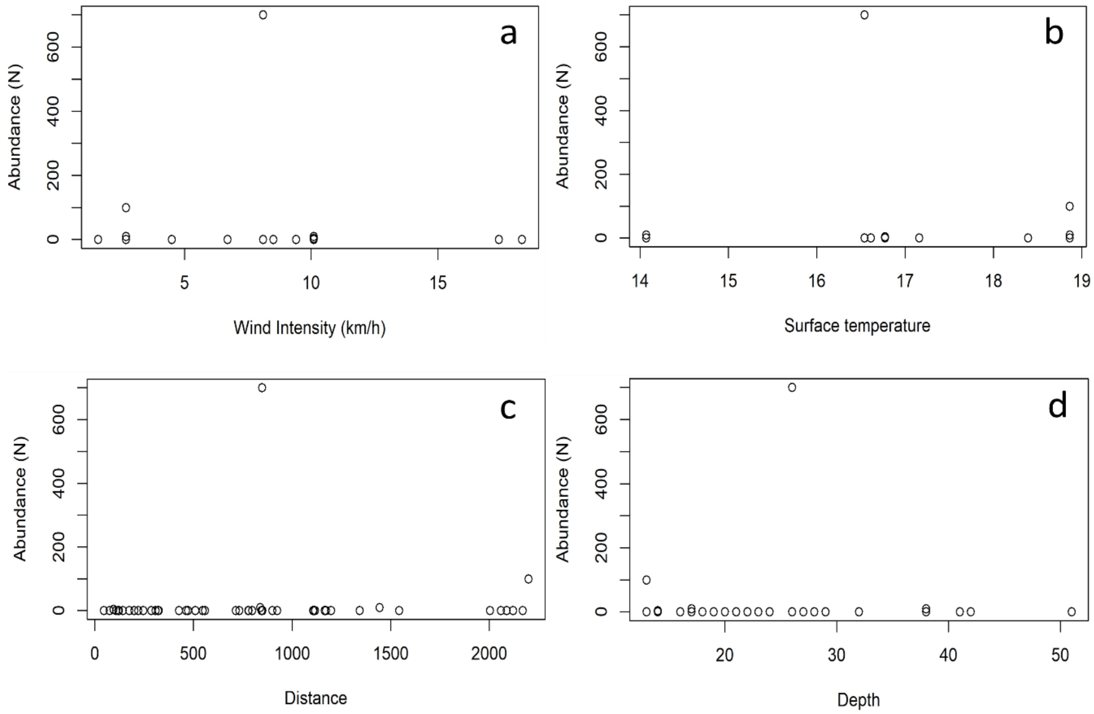
Supplementary figure 5 - Categorical variables analysis for *Diplodus cervinus*. (a. Tide; b. Moon; c. Sunlight; d. Wind Direction; e. Substrate; f. Rugosity)



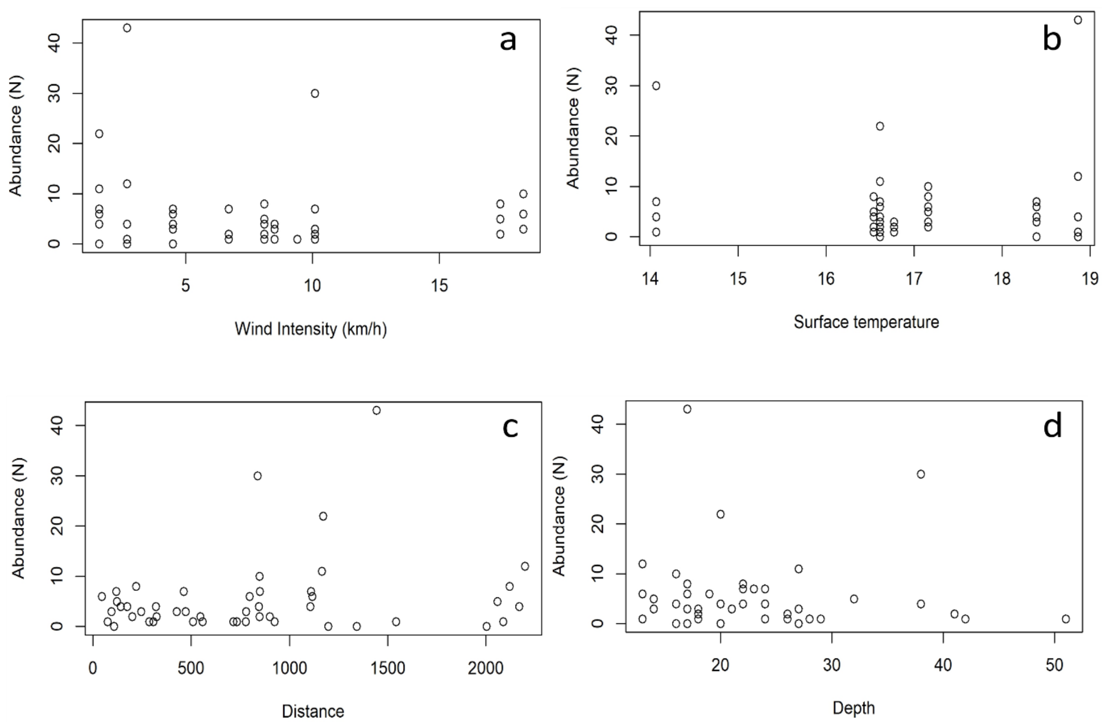
Supplementary figure 6 - Categorical variables analysis for *Spondyliosoma cantharus*. (a. Tide; b. Moon; c. Sunlight; d. Wind Direction; e. Substrate; f. Rugosity)



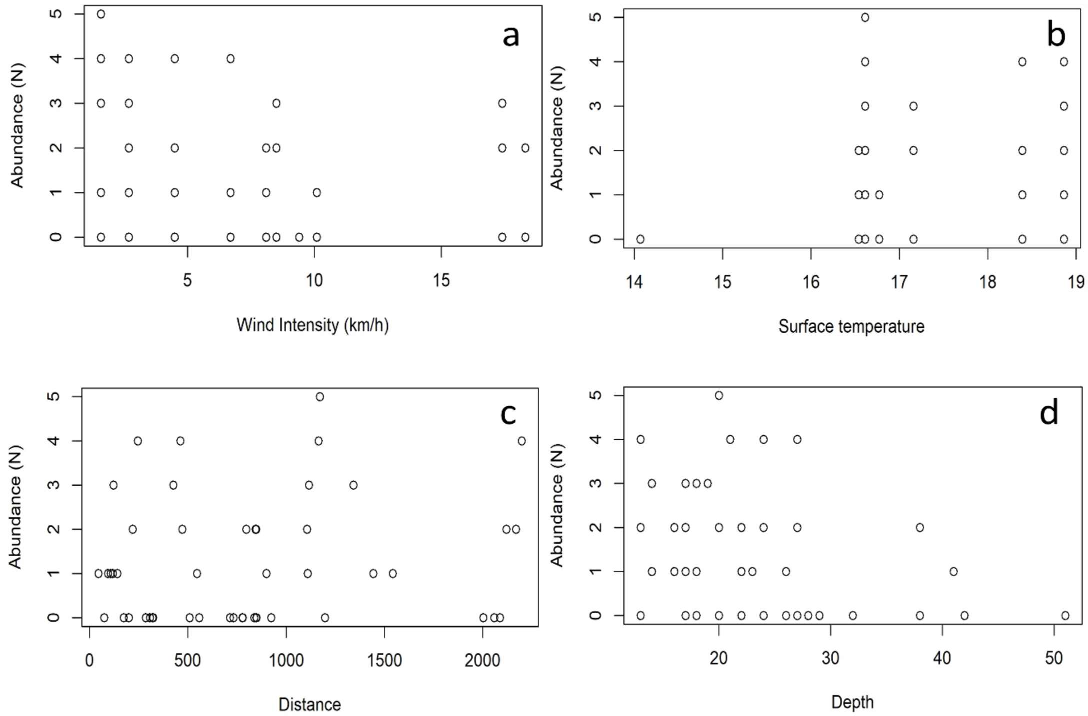
Supplementary figure 7 - Categorical variables analysis for *Octopus vulgaris*. (a. Tide; b. Moon; c. Sunlight; d. Wind Direction; e. Substrate; f. Rugosity)



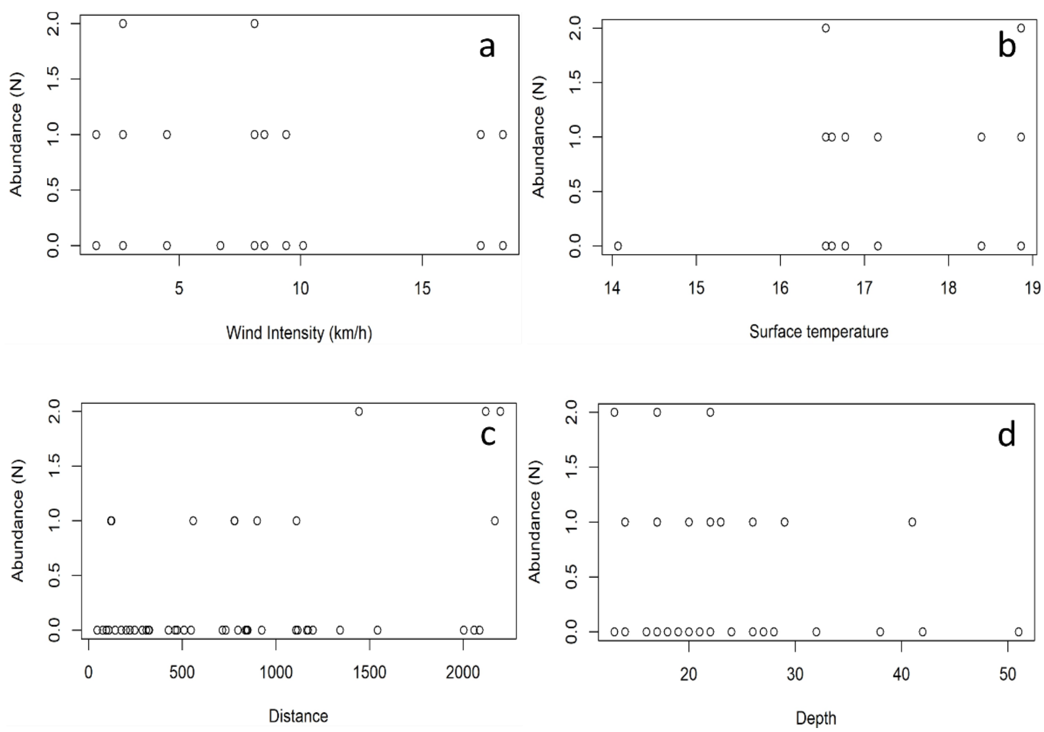
Supplementary figure 8 - Continuous variables analysis for *Dicentrarchus labrax*. (a. Wind Intensity; b. Surface temperature; c. Distance to shore; d. Depth)



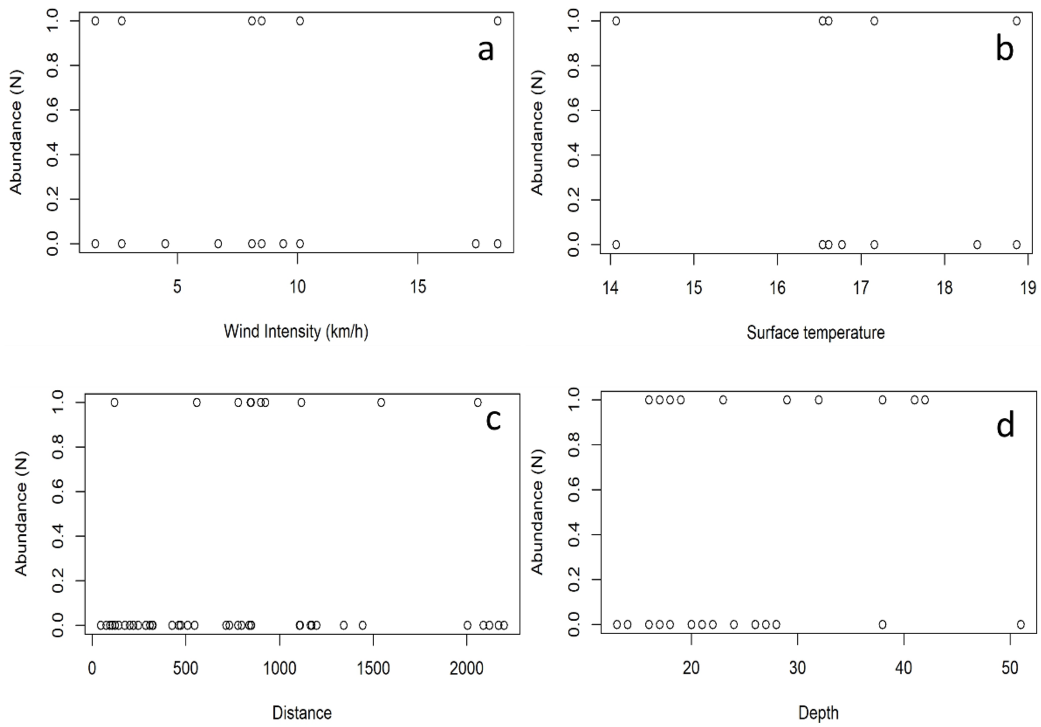
Supplementary figure 9- Continuous variables analysis for *Diplodus vulgaris*. (a. Wind Intensity; b. Surface temperature; c. Distance to shore; d. Depth)



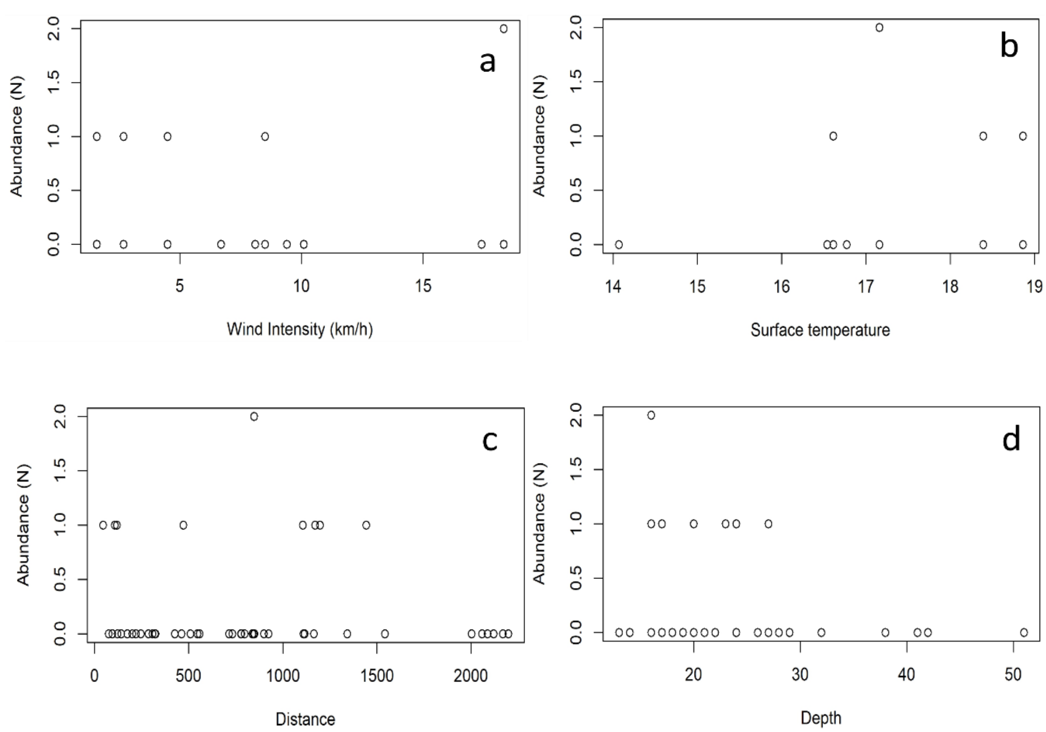
Supplementary figure 10 - Continuous variables analysis for *Diplodus sargus*. (a. Wind Intensity; b. Surface temperature; c. Distance to shore; d. Depth)



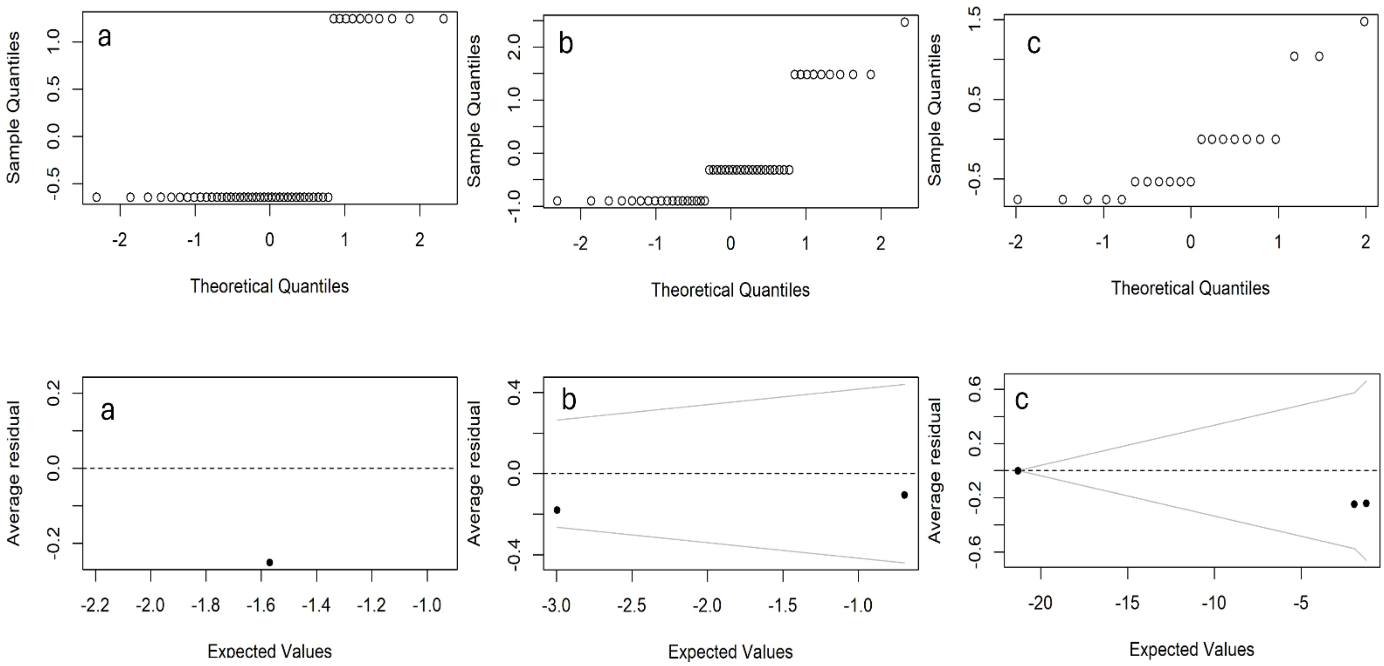
Supplementary figure 11 - Continuous variables analysis for *Diplodus cervinus*. (a. Wind Intensity; b. Surface temperature; c. Distance to shore; d. Depth)



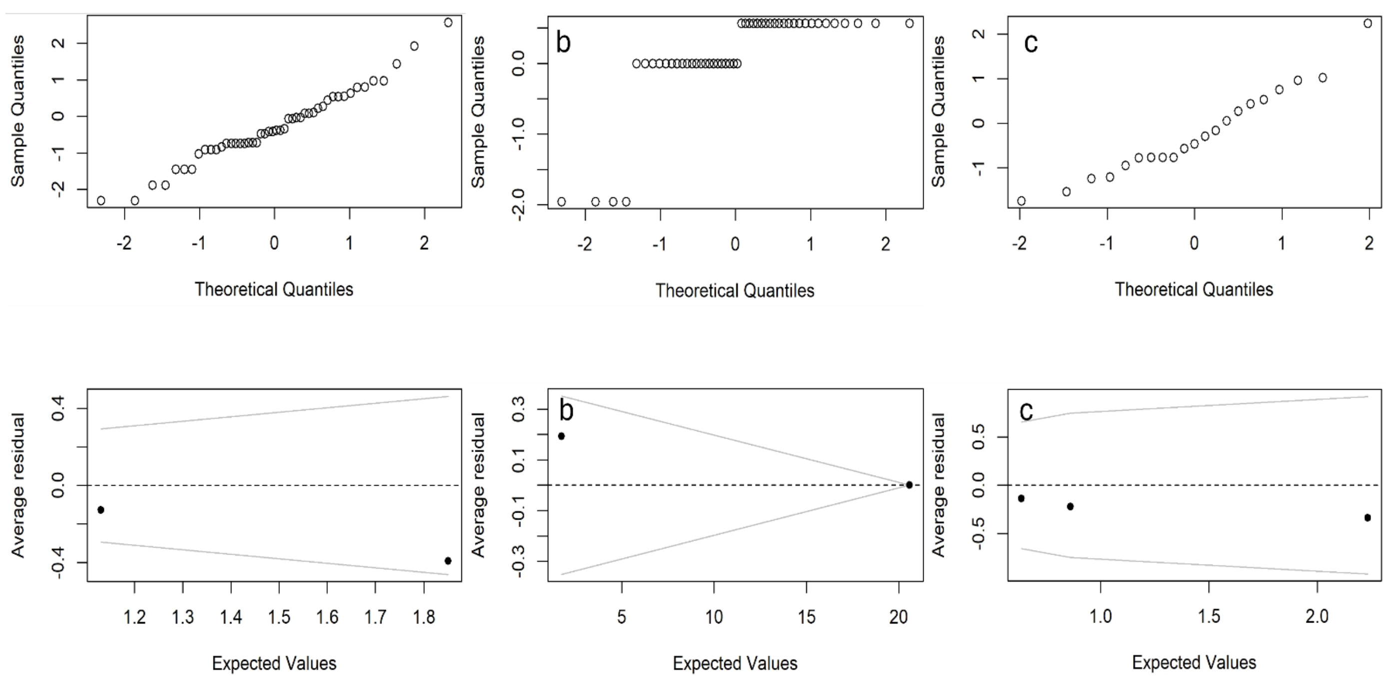
Supplementary figure 12 - Continuous variables analysis for *Spondyliosoma cantharus*. (a. Wind Intensity; b. Surface temperature; c. Distance to shore; d. Depth)



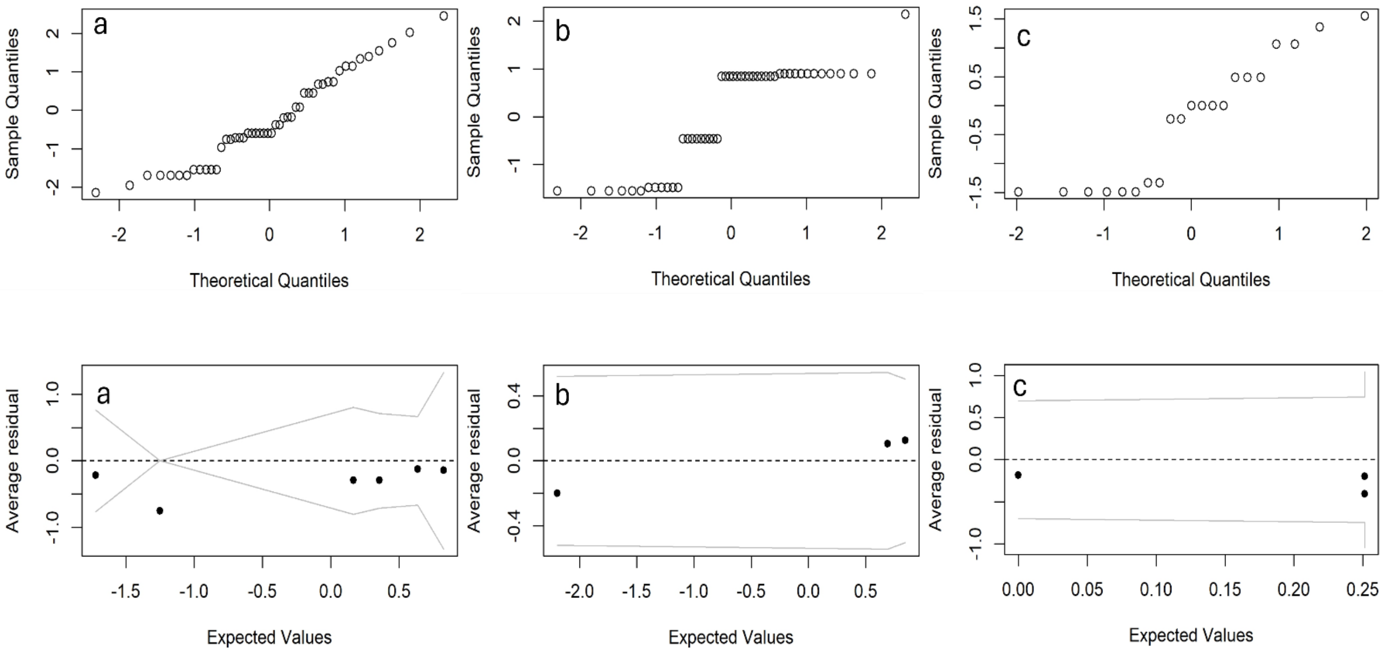
Supplementary figure 13 - Continuous variables analysis for *Octopus vulgaris*. (a. Wind Intensity; b. Surface temperature; c. Distance to shore; d. Depth)



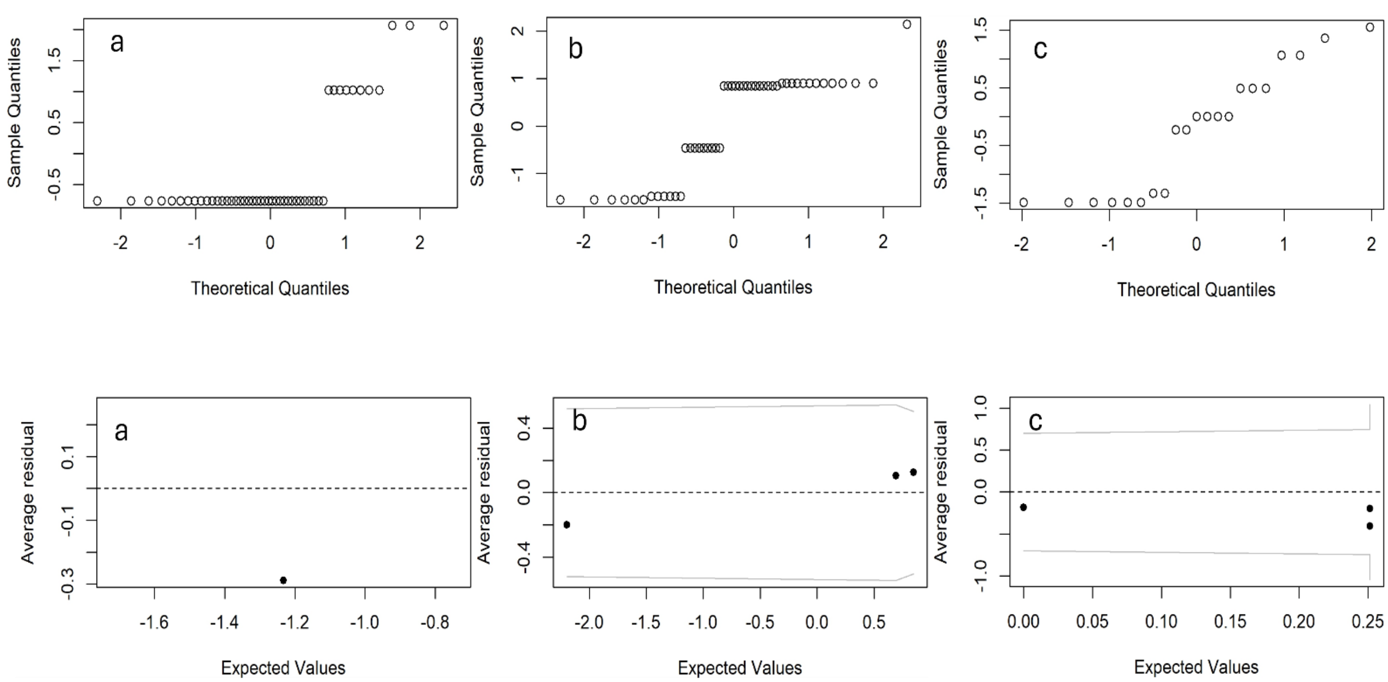
Supplementary figure 14 - GLM diagnostics for *Dicentrarchus labrax* (a. Abundance; b. Occurrence; c. Transects)



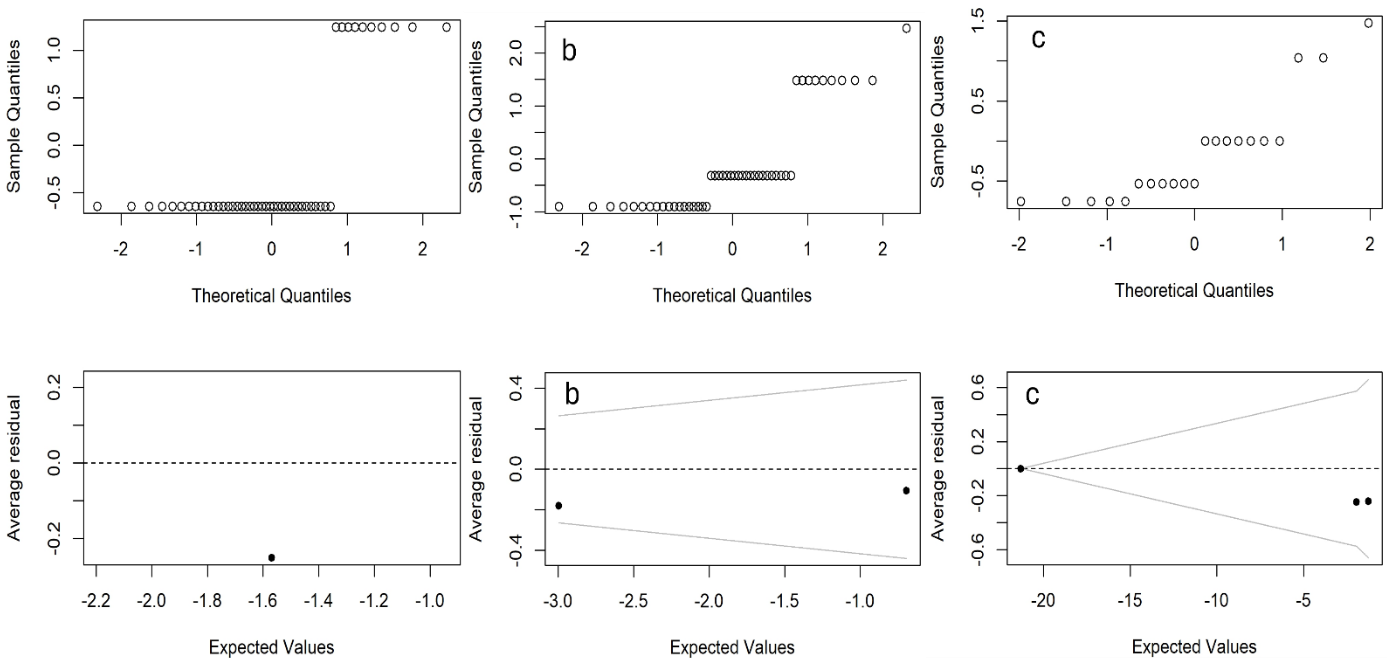
Supplementary figure 15 - GLM diagnostics for *Diplodus vulgaris* (a. Abundance; b. Occurrence; c. Transects)



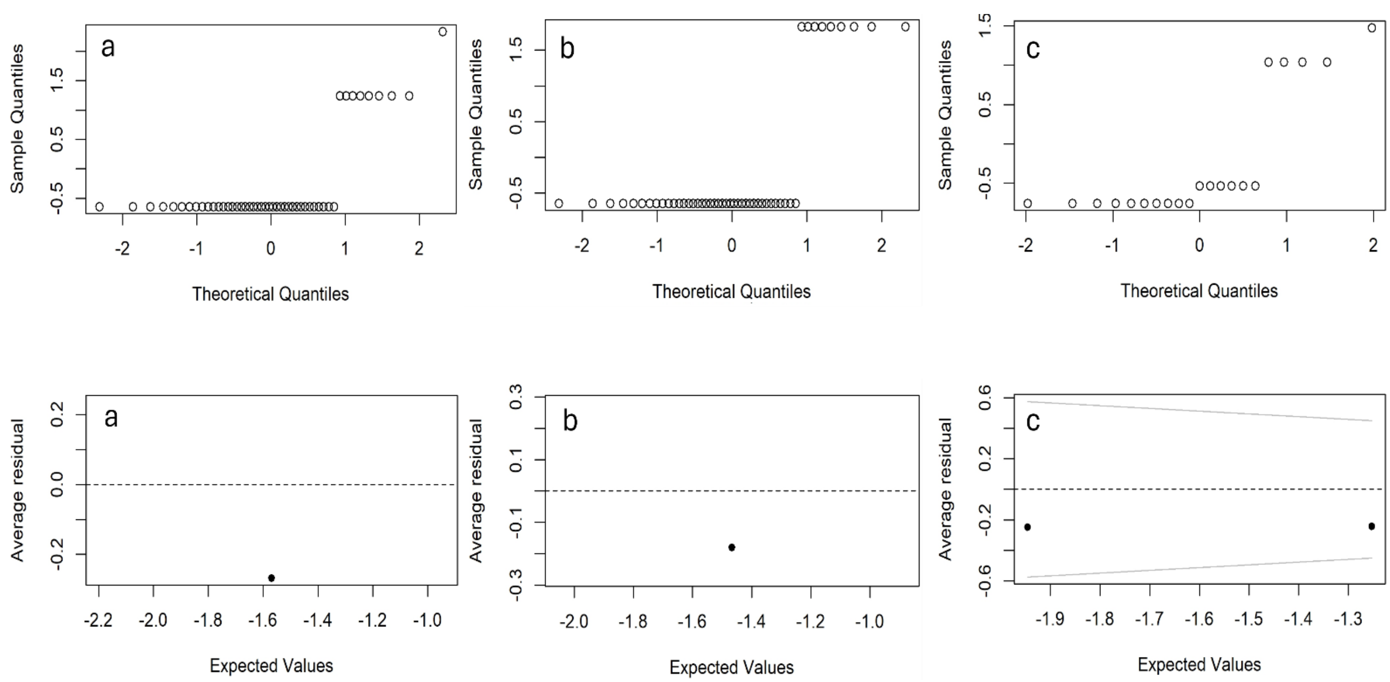
Supplementary figure 16 - GLM diagnostics for *Diplodus sargus*. (a. Abundance; b. Occurrence; c. Transects)



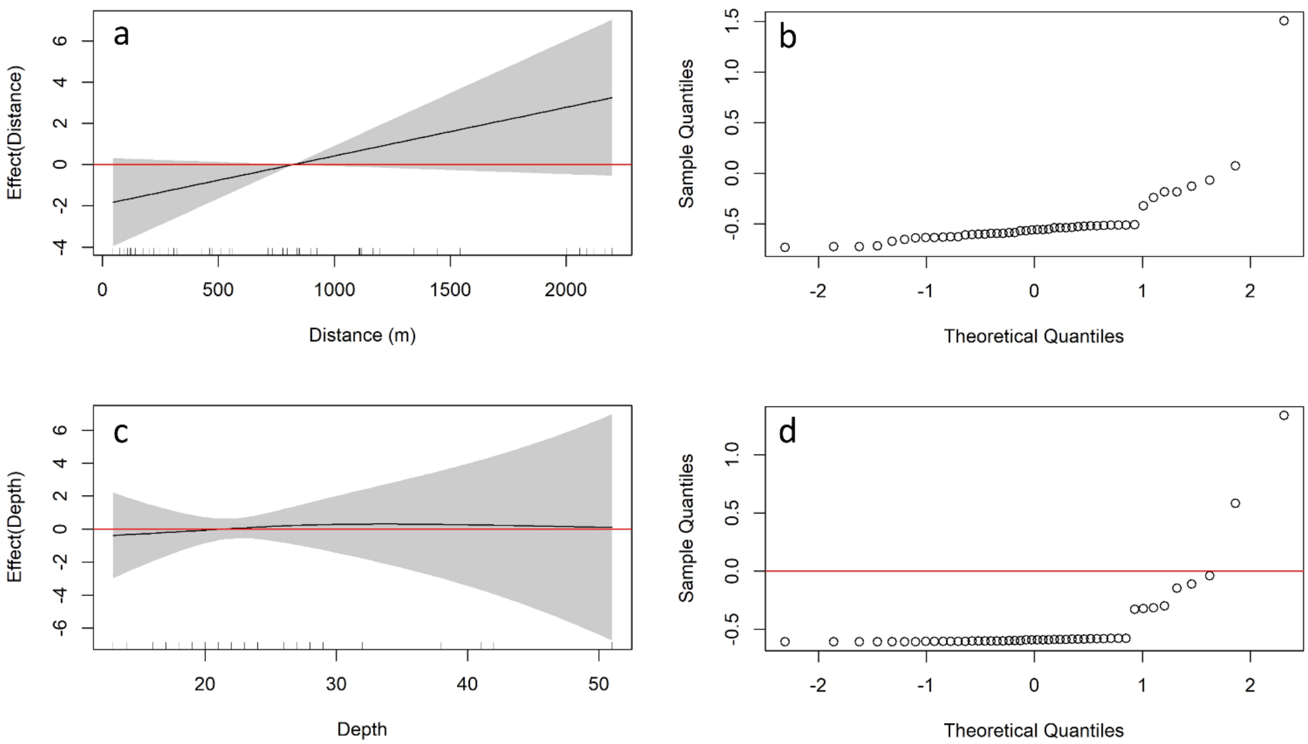
Supplementary figure 17 - GLM diagnostics for *Diplodus cervinus*. (a. Abundance; b. Occurrence; c. Transects)



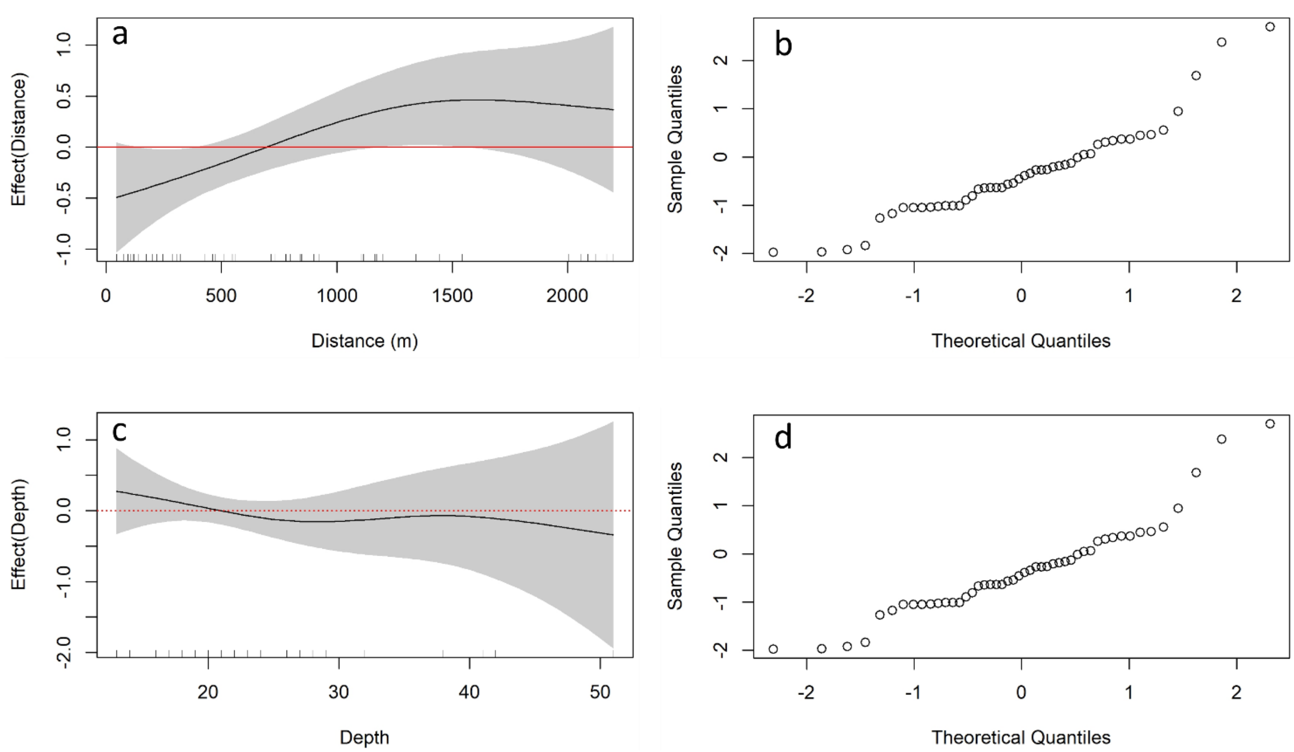
Supplementary figure 18 - GLM diagnostics for *Spondyliosoma cantharus*. (a. Abundance; b. Occurrence; c. Transects)



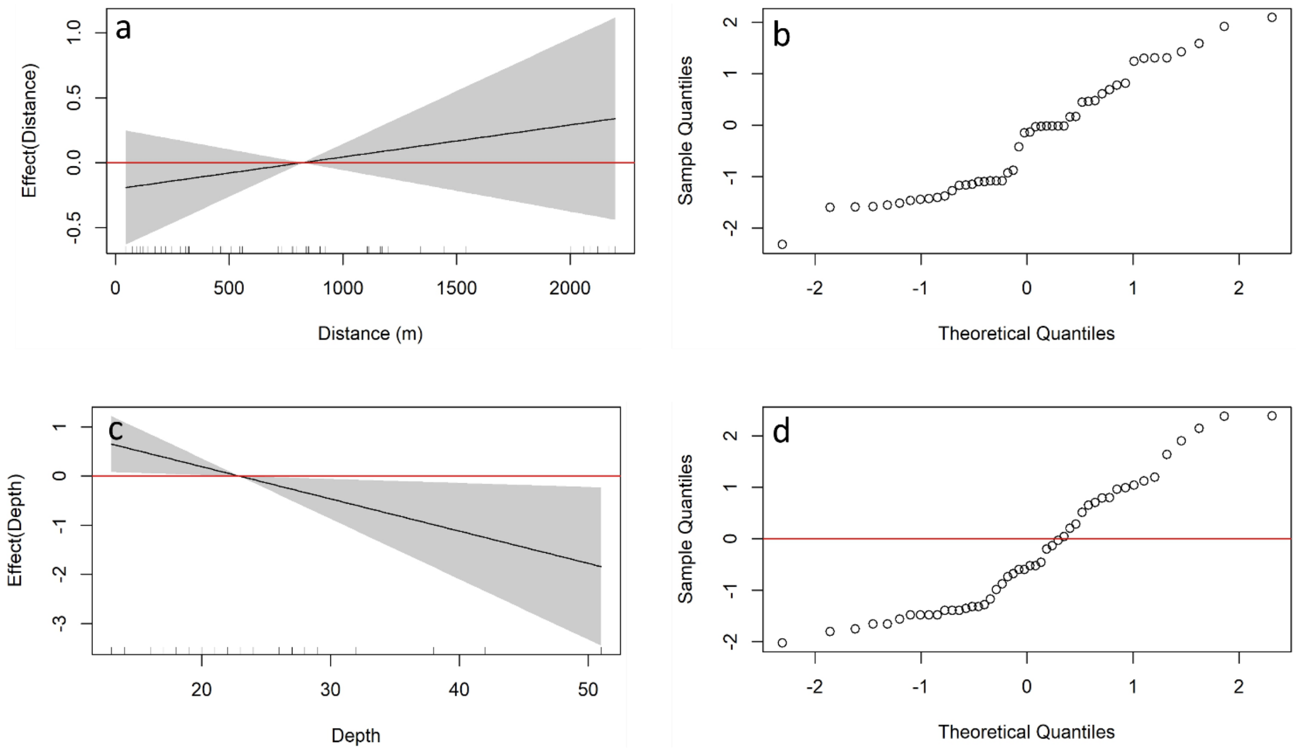
Supplementary figure 19 - GLM diagnostics for *Octopus vulgaris*. (a. Abundance; b. Occurrence; c. Transects)



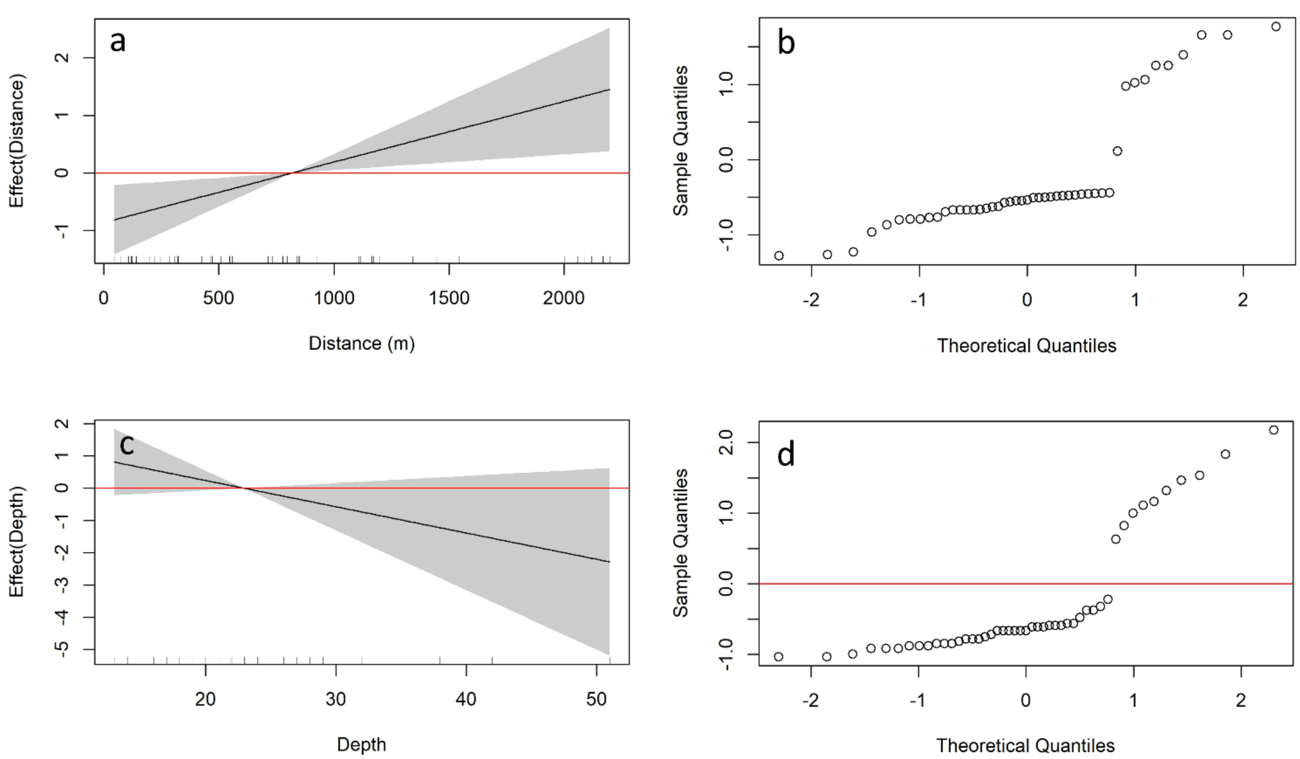
Supplementary figure 20 - GAM results (a. Distance to Shore; c. Depth) and residuals diagnostics (b. Distance to Shore; d. Depth) for *Dicentrarchus labrax*.



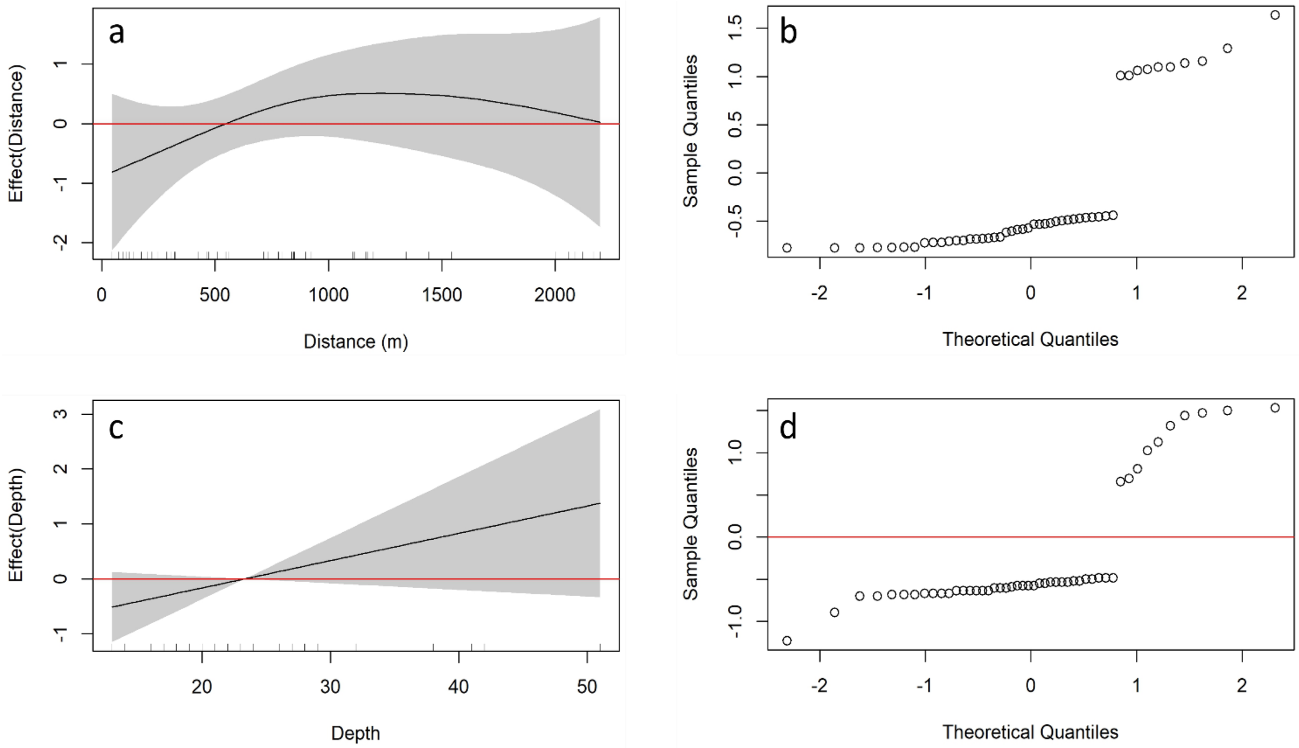
Supplementary figure 21 - GAM results (a. Distance to Shore; c. Depth) and residuals diagnostics (b. Distance to Shore; d. Depth) for *Diplodus vulgaris*.



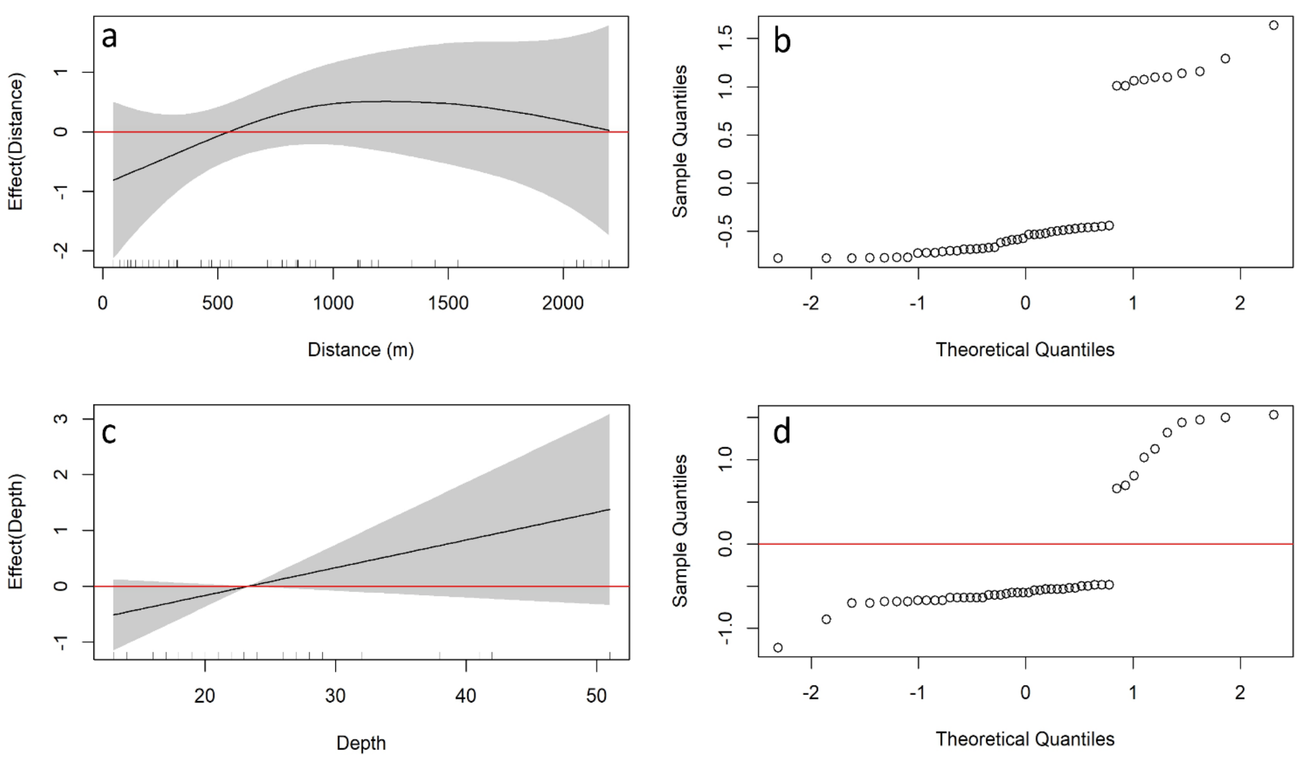
Supplementary figure 22 - GAM results (a. Distance to Shore; c. Depth) and residuals diagnostics (b. Distance to Shore; d. Depth) for *Diplodus sargus*.



Supplementary figure 23 - GAM results (a. Distance to Shore; c. Depth) and residuals diagnostics (b. Distance to Shore; d. Depth) for *Diplodus cervinus*.



Supplementary figure 24 - GAM results (a. Distance to Shore; c. Depth) and residuals diagnostics (b. Distance to Shore; d. Depth) for *Spondyliosoma cantharus*.



Supplementary figure 25 - GAM results (a. Distance to Shore; c. Depth) and residuals diagnostics (b. Distance to Shore; d. Depth) for *Octopus vulgaris*.

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