Management strategy evaluation using the individual-based, multispecies modeling approach OSMOSE

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Highlights

- We developed a management strategy evaluation framework for the OSMOSE model.
- We applied this framework to the West Florida Shelf ecosystem and red grouper.
- Alternative total allowable catch (TAC) strategies were evaluated for red grouper.
- Lower acceptable risks of overfishing resulted in higher biomass for red grouper.
- TAC update frequency impact was small in a context of episodic environmental events.

ABSTRACT

End-to-end ecosystem modeling platforms, including OSMOSE, are key tools for informing ecosystem-based fisheries management (EBFM). End-to-end models ideally implement two-way interactions between model components, yet two-way interactions between high trophic level (HTL) functional groups and humans (fisheries managers and fishers) are currently missing in OSMOSE. We developed a management strategy evaluation (MSE) framework for OSMOSE, which allows for feedback between HTL functional groups and fisheries managers. This framework couples OSMOSE to a management procedure integrating decision rules and accounting for scientific uncertainty and the acceptable risk of overfishing. We applied the MSE framework to the OSMOSE model of the West Florida Shelf, so as to conduct an evaluation of total allowable catch (TAC) strategies for red grouper (*Epinephelus morio*) in a context of episodic events of natural mortality. Our simulations indicate that TAC strategies that assume higher scientific uncertainty and/or lower acceptable risk of overfishing result in higher biomass-related metrics for red grouper. However, the levels of scientific uncertainty and acceptable risk of overfishing impose a trade-off between biomass-related and catch-related metrics for red grouper. Our simulations also indicate that updating red grouper TAC more frequently in a context of episodic events of natural mortality does not have a large impact on biomass-related and catch-related metrics for red grouper and other functional groups. The MSE we conducted for red grouper is strategic, and its outcomes, which were obtained under a specific set of assumptions, must be considered preliminary. We discuss how future research could help enhance understanding of the possible impacts of TAC strategies for red grouper. The MSE framework designed for OSMOSE links the dynamics of HTL functional groups to that of fisheries managers, thereby allowing OSMOSE to be better suited for informing EBFM. This framework is an invaluable asset in assessing the performance of fisheries management strategies, but could also be used for other purposes, such as the evaluation of research monitoring programs.

Keywords: management strategy evaluation; ecosystem modeling; end-to-end model; total acceptable catch; risk of overfishing; Gulf of Mexico

1. Introduction

Ecosystem-based fisheries management (EBFM), which recognizes the physical, biological and socio-economic complexities of managing marine resources, is gaining increasing momentum around the world (Pikitch et al., 2004; Link and Browman, 2014; Patrick and Link, 2015). End-to-end models of marine ecosystems, which attempt to represent an entire ecological system, including high trophic level (HTL) functional groups, low trophic level (LTL) organisms (e.g., plankton, benthos), humans (fisheries managers and fishers), and the associated abiotic environment, are key tools for influencing and strengthening EBFM (Travers et al., 2007; Fulton, 2010; Shin et al., 2010; Steele et al., 2013). Major end-to-end modeling platforms include the biogeochemical modeling approach Atlantis (Fulton et al., 2004, 2007, 2011), the trophodynamic modeling framework Ecopath with Ecosim (EwE) with Ecospace (Pauly et al., 2000; Christensen and Walters, 2004; Steenbeek et al., 2016), and the individual-based, multi-species modeling approach OSMOSE (Object-oriented Simulator of Marine ecOSystem Exploitation) (Travers-Trolet et al., 2014a; Grüss et al., 2016). Atlantis, EwE with Ecospace and OSMOSE are increasingly being used worldwide, in particular to conduct multi-model evaluations of the ecosystem impacts of fishing (Travers et al., 2010; Smith et al., 2011, 2015; Shin et al., 2012).

End-to-end ecosystem models are more appealing for addressing issues related to EBFM if they implement two-way interactions between model components, including between LTL and HTL functional groups and between HTL functional groups and humans (Travers et al., 2007; Travers et al., 2010; Rose, 2012). Within the Atlantis modeling platform, numerous sub-models simulate features and processes crucial to a functioning marine ecosystem, allowing Atlantis to easily bridge LTL, HTL and human drivers and processes (Fulton et al., 2011). Moreover, recent developments enable EwE with Ecospace to implement two-way interactions if need be (Steenbeek et al., 2016). These recent developments include an implementation of EwE in the Fortran programming language for permitting feedback between HTL and LTL functional groups (Akoglu et al., 2015), the capability to couple EwE with Ecospace to a management procedure (Dichmont et al., 2013), and the integration of a fishing fleet dynamics sub-model into Ecospace (de Mutsert et al., 2015). By contrast, two-way interactions between LTL and HTL functional groups and between HTL functional groups and humans are currently nonexistent or limited in OSMOSE models. OSMOSE applications generally represent LTL functional groups in the form of biomass fields serving as potential food for HTL functional groups, with no feedback between HTL and LTL groups (Marzloff et al., 2009; Brochier et al., 2013; Fu et al., 2013; Grüss et al., 2015, 2016). An exception to this general pattern is the most recent Southern Benguela application of OSMOSE, where the individual-based model simulating the dynamics of HTL functional groups is two-way coupled to a biogeochemical model, allowing the biomasses of plankton groups to vary in response to predation by HTL functional groups (Travers-Trolet et al., 2014a, 2014b). Furthermore, there is currently no two-way interaction between HTL functional groups and humans in OSMOSE, despite the fact that fishing mortality rates or fisheries catches can be substantially altered in the real world as a management response to changes in the biomass of HTL functional groups. For example, in the United States (U.S.), the 2006 reauthorization of the Magnuson-Stevens Fishery Conservation and Management Act (MSA) requires the regular update of total allowable catches (TACs) based on the probability of overfishing of the target species (MSRA, 2006; Federal Register, 2008). Therefore, there is a pressing need to link the dynamics of the HTL functional groups represented in OSMOSE to actions taken by humans, so as to enhance the capability of OSMOSE as an end-to-end modeling approach to provide advice for EBFM.

The development of a management strategy evaluation (MSE) framework for OSMOSE would offer an opportunity to implement two-way interactions between HTL functional groups and fisheries managers. MSE is a process designed to simulate alternative fisheries management strategies and to identify those strategies that are robust to uncertainties and natural variation and that balance management objectives (Smith et al., 1999; Kell et al., 2007; Butterworth et al., 2010; Holland, 2010; Bunnefeld et al., 2011; Punt et al., 2014). MSE involves the two-way coupling of an "operating model" generating "true" ecosystem dynamics, including natural variations in the study system, with a management procedure (MP) dictating fisheries management measures such as TACs, target fishing mortality rates, or fishing effort limits (Smith, 1994; Schnute et al., 2007; Kraak et al., 2008). The core of the MP is a decision rule, which dynamically modifies management actions based on the data sampled from the operating model and specific stock assessment methods (Punt, 2006; Schnute et al., 2007; Holland, 2010). It is also possible to integrate into an MSE framework an implementation model accounting for the fact that the fisheries catches, fishing mortality rates or fishing efforts prescribed by the MP may be exceeded or may not be achieved in the real world due to, e.g., poor enforcement or fisher behavior (Holland, 2010, Bunnefeld et al., 2011). Many MSE frameworks integrate an assessment model, while others do not. However, those MSE frameworks that do not integrate an assessment model generally account for stock assessment error or uncertainty in stock assessments (Baldursson et al., 1996; Danielsson et al., 1997; Punt, 2006; Holland, 2010; Punt et al., 2014; Steenbeek et al., 2016). For example, the MSE framework developed by Baldursson et al. (1996) and Danielsson et al. (1997) for evaluating TAC strategies for Icelandic cod (*Gadus morhua*) merely mimics uncertainty in stock assessments.

In the present study, we introduce the MSE framework that we developed for the OSMOSE modeling platform, and we then apply this framework to the OSMOSE model of the West Florida Shelf in the Gulf of Mexico (GOM) for the 2000s ("OSMOSE-WFS") (Grüss et al., 2015, 2016). Our MSE framework currently does not include an assessment model (although it does account for uncertainty in stock assessments and includes observation and implementation errors); it is essentially limited to fisheries management actions through decision rules applied to OSMOSE output, since the primary intent of the current MSE framework for OSMOSE is the simulation and strategic testing of alternative TAC strategies. In the following, we first provide an overview of the OSMOSE modeling approach, which helps elucidate the decisions made regarding the structure and assumption of our MSE framework. We then present the MSE framework that we designed for OSMOSE. Next, we briefly describe the current version of the OSMOSE-WFS model, before applying our MSE framework to red grouper (*Epinephelus morio*), a species of high economic importance in the GOM. Finally, we discuss the strengths, limitations and perspectives of our work.

2. Material and methods

2.1. The OSMOSE modeling approach

OSMOSE is a two-dimensional, individual-based, multi-species modeling approach which explicitly simulates the whole life cycle of the major HTL functional groups of an ecosystem (Shin and Cury, 2001, 2004). Its primary characteristic is that it does not specify the diet compositions of HTL groups *a priori* but rather assumes that predation is an opportunistic and size-based process, letting food web structure emerge from local predation and competition interactions (Shin and Cury, 2001, 2004; Grüss et al., 2016). More precisely, predation in OSMOSE depends on: (1) the overlap between predators and potential prey in the horizontal dimension; (2) size adequacy between the predators and the potential prey (this being determined by "predator/prey size ratios"); and (3) the accessibility of prey to predators related to their vertical distribution and morphology (this being determined by means of "accessibility coefficients").

The basic units of OSMOSE are schools, which are composed of individuals that belong to the same HTL group, and that have the same age, length and food needs and, at a given time step, the same geographical coordinates (Shin and Cury, 2001, 2004). Thus, the architecture of the HTL community in OSMOSE is hierarchical and organized around four model classes: a "school" belongs to an age class ("cohort"), which itself belongs to a "HTL group", which itself belongs to the HTL community. Such a hierarchical architecture enables the computation of output variables at different levels of aggregation (e.g., body length and biomass can be assessed at the levels of the age group, HTL group and HTL community; Shin et al., 2004; Travers et al., 2007; Marzloff et al., 2009; Grüss et al., 2015). Due to the fact that each school simulated in OSMOSE is represented from the egg stage to the terminal age, which necessitates intensive calculation capacities and the integration of comprehensive information on entire life cycles, usually no more than 15 HTL groups are explicitly considered in OSMOSE models.

Functional groups that are not explicitly considered in OSMOSE, i.e., LTL functional groups (plankton, benthos) and HTL organisms such as seabirds and marine mammals, are implicitly taken into account in the modeling platform. The mortality of schools comprises fishing mortality, predation mortality, starvation mortality, and diverse natural mortality ($M_{diverse}$) due to causes other than starvation and predation by the HTL groups represented in OSMOSE, i.e., catastrophic events such as red tides and predation by organisms not considered in OSMOSE (e.g. seabirds and marine mammals) (Shin and Cury, 2001, 2004; Grüss et al., 2015). Moreover, in OSMOSE, LTL groups are considered in the form of biomass fields serving as potential food for the HTL groups that are explicitly represented in the modeling platform (Appendix A).

The current version of the OSMOSE modeling platform is "OSMOSE version 3 update 2" or "OSMOSE v3u2", which essentially differs from the previous version of

OSMOSE ("OSMOSE version 3 update 1" or "OSMOSE v3u1") in that it employs a "seeding process" to initialize the modeled system (Appendix A). In OSMOSE v3u2, four successive major events occur: (1) distribution of the schools in the horizontal dimension using specific distribution maps; (2) mortalities (fishing mortality, predation mortality, starvation mortality, and diverse natural mortality $M_{diverse}$); (3) somatic growth of schools based on their predation success; and (4) reproduction. Currently, fishing mortality rates rather than fisheries catches are used in OSMOSE to simulate the fishing mortality process. OSMOSE is a stochastic modeling approach due to the distribution of limited numbers of schools in the horizontal dimension based on distribution maps, the implementation of random walk movements within the distribution areas of schools, and the computation of mortality rates using a "stochastic mortality algorithm" (Grüss et al., 2016). The details of OSMOSE v3u2 can be found in Appendix B.

OSMOSE is written in the Java programming language. The input files provided to OSMOSE are CSV and netCDF files (http://www.osmose-model.org). Some of the CSV files specify time series of fishing mortality rates or $M_{diverse}$, which are useful to simulate mortality scenarios with OSMOSE. It is also possible to define multipliers of LTL group biomasses to simulate scenarios of environmental change with OSMOSE.

2.2. MSE framework for OSMOSE

We developed a relatively simple MSE framework for OSMOSE v3u2. Its core is the specification of total allowable catches (TACs) or target fishing mortality rates using a decision rule and a buffer accounting for scientific uncertainty and the risk of overfishing considered acceptable (Fig. 1). The MSE process involves the following eight steps (Fig. 1):

(Step 1) OSMOSE is run to a steady-state, where the biomasses of all HTL groups have reached equilibrium, at which point information on the modeled system is saved. This step requires a fully calibrated OSMOSE model with the fishing mortality rates of all HTL groups, including those targeted by management efforts, maintained at their baseline (i.e., current) value.

(Step 2) OSMOSE is restarted from its steady-state and runs until the time of implementing a management strategy comes.

(Step 3) When the time of implementing a management strategy comes, OSMOSE is paused, and the spawning stock biomasses (SSBs) of the HTL groups targeted by management efforts are sampled from OSMOSE to generate estimates of observed SSBs that are provided to a management procedure (MP). This step requires a sampling module mimicking research surveys, which currently consists of applying a lognormal error with a mean of the log μ_{survey} and a standard error of the log σ_{survey} to the SSBs provided by OSMOSE, as is often done in single-species MSE frameworks (Kraak et al., 2010; McGilliard et al., 2011; Punt et al., 2014). Estimates for μ_{survey} and σ_{survey} can be obtained, e.g., from fisheries stock assessments.

(Step 4) Within the MP, limit fishing mortality rates (F_{lim}) or catch limits (overfishing limits or OFLs) are determined from the observed SSBs, using a specific decision rule integrating reference points (e.g., the maximum sustainable yield (MSY), and the SSB at the annual fishing mortality rate resulting in MSY (SSB_{msy})) (Fig. 2). We developed a framework to produce reference points from OSMOSE for the MSE process (see Subsection 2.2.1).

(Step 5) Target fishing mortality rates or TACs are determined from F_{lim} or OFLs, respectively, using a buffer reflecting scientific uncertainty and an acceptable risk of overfishing. As is usually the case in existing MSE frameworks, scientific uncertainty refers here to uncertainty around limit reference points, i.e., F_{lim} or OFL, which are assumed to be lognormally distributed with the standard error of the log given by σ_{OFL} (Prager and Shertzer, 2010; Ralston et al., 2011; Punt et al., 2012; Gulf of Mexico Fishery Management Council, 2014). One way to estimate the parameter σ_{OFL} is to quantify the uncertainty associated with fitting stock assessment models to data (Punt et al., 2012). However, such a quantification of scientific uncertainty usually results in distributions of F_{lim} or OFL that are very tight (Ralston et al., 2011; Punt et al., 2012). Ralston et al. (2011) estimated σ_{OFL} for species of the U.S. west coast by quantifying variation among multiple assessments of the same stock. The mean σ_{OFL} of species of the U.S. west coast was found to be 0.36 (Ralston et al., 2011). Moreover, the risk of overfishing considered acceptable is generally determined by fisheries managers, but methodologies exist to quantify this risk, based on data availability and various criteria such as life-history characteristics that increase vulnerability, time since the last stock assessment, and stock status (Prager and Shertzer, 2010; Ralston et al., 2011; Punt et al., 2012).

(Step 6) The target fishing mortality rates or TACs are passed to an implementation module, which determines effective fishing mortality rates or effective TACs, taking into account implementation error. The implementation module currently consists of applying a lognormal error with a mean of the log μ_{imp} and a standard error of the log σ_{imp} to the target fishing mortality rates or TACs prescribed by the MP, as is often done in single-species MSE frameworks (e.g., Shertzer et al., 2008, 2010; Schirripa, 2015). Estimates for μ_{imp} and σ_{imp} can be obtained, e.g., from a retrospective analysis comparing past TACs to achieved fisheries catches.

(Step 7) The effective fishing mortality rates or effective TACs are delivered to OSMOSE, which restarts from where it was paused and runs until the time of evaluation comes.

(Step 8) Steps 3 to 7 are repeated until the final year of simulations is reached (Fig. 1).

The framework detailed above necessitates a two-way coupling between OSMOSE and the MP. This two-way coupling is achieved on a cluster of calculations, where a Java executable file encapsulating OSMOSE can communicate with the R software environment where the sampling module, MP and implementation module are implemented. The implementation of the MSE framework on a cluster of calculations is critical, given that hundreds of OSMOSE replicates must be run for each scenario considered within the MSE process (See Subsection 2.2.2).

Modifications were needed in the Java code of OSMOSE v3u2 to: (1) enable OSMOSE to be paused and restarted; and (2) implement fisheries catches for the HTL groups targeted by management efforts rather than apply fishing mortality rates when the MP provides TACs to OSMOSE. First, changes in the Java code were made to save information on all schools (i.e., abundance, body length, weight, etc.) in netCDF files when the time of implementing a management strategy comes (i.e., when OSMOSE is paused and SSB estimates are passed to the MP). These netCDF files are used along with OSMOSE input files to ensure that OSMOSE restarts exactly from where it paused, putting aside the fact that the fishing mortality rates or fisheries catches of the HTL groups targeted by management efforts are updated (Fig. 1). Moreover, changes were introduced in the OSMOSE Java code to be able to implement fisheries catches for the HTL groups targeted by management efforts rather than apply fishing mortality rates to these HTL groups when the MP provides TACs rather than target fishing mortality rates to OSMOSE. These changes allow one to: (1) identify all the fishable schools of the HTL group under consideration, so as to determine the fishable biomass of that HTL group; and (2) compute the catch in biomass of each school *s* of the HTL group from the TAC for that group, the seasonality of fisheries catches, the biomass of school *s*, and the fishable biomass of the HTL group. These computations make the assumption that fishing mortality is distributed uniformly over space, which is also the assumption that is being made when fishing mortality rates rather than fisheries catches are provided to OSMOSE (Appendix B). In reality, the spatial distribution of fishing mortality is very rarely uniform, since fishers allocate their fishing effort spatially based on anticipated costs or benefits. The simplistic assumption made in OSMOSE that fishing mortality is distributed uniformly over space could be addressed through: (1) the provision of spatial heterogeneous patterns of fishing effort to OSMOSE; or (2) the integration of fishers as explicit components (i.e., objects) of the modeling platform and the simulation of fishers' behavior.

2.2.1. Preliminary steps to the MSE process

Preliminary steps to the MSE process include: (1) the initiation of interactions with fisheries managers and other stakeholders; and (2) the estimation of reference points.

Interactions with fisheries managers and other stakeholders are paramount to the success of an MSE process (Punt et al., 2014). The MSE process and the scenarios tested within this process must be designed around the main concerns of stakeholders (Holland, 2010; Punt et al., 2014; Schirripa, 2015), which ensures the selection of pertinent decision rules and acceptable risks of overfishing within the MSE framework (Holland, 2010; Punt et al., 2014). Moreover, discussions with fisheries managers and other stakeholders allow the identification of a focused set of critical performance metrics, which facilitate the communication of MSE outcomes (Holland, 2010; Plagányi et al., 2014; Punt et al., 2014).

Reference points are necessary to the parameterization of decision rules in the MSE framework. Such reference points can include the annual fishing mortality rate resulting in MSY (F_{msy}) and SSB_{msy}, but also annual fishing mortality rates and SSBs at which the spawning potential ratio (SPR, i.e., the ratio of SSB per recruit over unfished SSB per recruit) reaches a certain percentage. The equation of SSB per recruit (SSBR) is given in Appendix C.

We developed a framework for the estimation of reference points with OSMOSE on a cluster of calculations. Within this framework, the annual fishing mortality rate of a HTL group targeted by management efforts is varied from 0 to 2 year^{-1} in increments of 0.01 while holding the annual fishing mortality rates of all the other HTL groups represented in OSMOSE at their baseline (i.e., current) values. Subsequently, the resulting SSBs, fisheries catches, mortality rates at age and weight of mature individuals at age at equilibrium are estimated. Then, SSBR as a function of annual fishing mortality rate is calculated for the HTL groups targeted by management efforts, according to Eq. C.1. Finally, generalized additive models using penalized cubic regression splines (Wood, 2006) are fitted to simulated SSB, fisheries catch and SSBR data points, from which MSY, F_{msy}, SSB_{msy}, SPR, and the annual fishing mortality rates and SSBs at which SPR reaches a certain percentage are estimated. The procedure for estimating reference points described here is a relatively standard procedure in the field of ecosystem modeling (Kaplan et al., 2013; Smith et al., 2014; Moffitt et al., 2015; Grüss et al., 2016).

2.2.2. Consideration of stochasticity and construction of scenarios

Because OSMOSE is a stochastic modeling approach, predictions can vary substantially from one OSMOSE run to another. Therefore, multiple OSMOSE replicates (ideally 100 or more) must be run under a given scenario within the MSE process.

The scenarios considered within the MSE process depend on the questions to be tackled to address the concerns of fisheries managers and other stakeholders. These scenarios can include management scenarios, pertaining, e.g., to the values attributed to the σ_{OFL} parameter and to the risk of overfishing considered acceptable, or the frequency of TAC updates. Scenarios can also include environmental variability if stakeholders are concerned with phenomena such as episodic events of natural mortality (e.g., red tides) or climate change. The simplest and quickest option to simulate environmental changes is to alter time series of $M_{diverse}$ or multipliers of LTL group biomasses directly in OSMOSE.

2.3. Application of the MSE framework

2.3.1. The OSMOSE-WFS model

OSMOSE-WFS is an OSMOSE model of the West Florida Shelf for the 2000s period, which has been developed within the Gulf of Mexico Integrated Ecosystem Assessment (IEA) program (Schirripa et al., 2012; Samhouri et al., 2014) (Fig. 3). The model is extensively described in Grüss et al. (2015, 2016). Therefore, we provide here only a brief presentation of OSMOSE-WFS. The OSMOSE-WFS model considered in the present study was parameterized with fishing mortality rates. Its parameterization is described in Appendix D.

OSMOSE-WFS explicitly represents the whole life cycle of the major pelagic-demersal and benthic HTL groups of the West Florida Shelf ecosystem. Ten fish groups and two crustacean HTL groups are explicitly considered in OSMOSE-WFS as either single species or groups of species (listed in Table 1). Grüss et al. (2016) identified three categories of HTL groups in the West Florida Shelf ecosystem with OSMOSE-WFS: (1) “large predators”, comprised of king mackerel (*Scomberomorus cavalla*), amberjacks, red grouper, gag grouper (*Mycteroperca microlepis*), and red snapper (*Lutjanus campechanus*); (2) “small predators”, consisting of reef carnivores, and large crabs; and (3) “forage fish and invertebrates”, including the sardine-herring-scad complex, anchovies/silversides, coastal omnivores, reef omnivores, and shrimps (Table 1). OSMOSE-WFS is forced by the biomasses of nine LTL groups (plankton and benthos groups), which were estimated from SeaWiFS (Sea-viewing Wide Field-of-view Sensor) data and an Ecopath model of the West Florida Shelf (“WFS Reef fish Ecopath”; Chagaris, 2013; Chagaris et al., 2015).

The version of the OSMOSE-WFS model considered in the present study uses OSMOSE v3u2. To meet the specifics of OSMOSE v3u2, the OSMOSE-WFS model presented in Grüss et al. (2016), which uses OSMOSE v3u1, was updated and recalibrated so that biomasses of the HTL groups represented in the model matched biomasses observed on the West Florida Shelf in the 2000s. As in Grüss et al. (2015, 2016), we employed a recently developed evolutionary algorithm (EA) (Oliveros-Ramos, 2014) to recalibrate OSMOSE-WFS. Details about the EA and the calibration process of OSMOSE-WFS can be found in Grüss et al. (2015). Once OSMOSE-WFS was recalibrated, we evaluated the model by comparing the predicted diet compositions to observed diets, and the predicted trophic levels (TLs) to TLs from the WFS Reef fish Ecopath model, as was done in Grüss et al. (2015, 2016). The evaluation process yielded results very similar to those reported in Grüss et al. (2016) and validated the new OSMOSE-WFS model. This is not surprising since the only major difference between OSMOSE v3u1 and OSMOSE v3u2 is the implementation of a seeding process in OSMOSE v3u2 to initialize the modeled system.

2.3.2. Application of the MSE framework to red grouper

We applied the MSE framework described above to GOM red grouper, a fish population of high economic importance. In the U.S. waters of the GOM, almost all red groupers are found on the West Florida Shelf (Coleman et al., 1996, 2011; Lombardi-Carlson et al., 2008; Sagarese et al., 2014); it is therefore appropriate to employ OSMOSE-WFS to conduct an MSE for GOM red grouper.

In June 2014, the Gulf of Mexico Fishery Management Council (GMFMC)'s Scientific and Statistical Committees (SSCs) passed a motion recommending that the GOM IEA program work with the SSCs to evaluate TAC strategies for GOM red grouper and determine how these strategies perform in a context of episodic events of natural mortality (due to, e.g., red tides, oil spill, or release of contaminants). This motion was motivated by field observations of red grouper mortality following severe red tides on the West Florida Shelf (Driggers et al., 2016) and explicit consideration of red tide mortality within the red grouper stock assessment model (SEDAR 42, 2015). In response to this motion, the GOM

IEA team interacted with the fisheries managers and other stakeholders (fishing industry and non-governmental organization representatives) during the GMFMC's SSC meetings that took place in 2014 and 2015, so as to develop MSE frameworks and select pertinent performance metrics to communicate MSE outcomes. The OSMOSE MSE framework applied to red grouper builds upon these interactions. Two other MSE frameworks are currently being developed within the GOM IEA program: one using a single-species model simulating the population dynamics of red grouper, and one using the Atlantis model of the GOM ("Atlantis-GOM"; Ainsworth et al., 2015). MSE frameworks designed within the GOM IEA program will complement red grouper stock assessments, especially because GOM red grouper assessments run projections that do not integrate two-way interactions between the resource and fisheries managers, contrary to MSE. We identified three questions to address with the OSMOSE MSE framework: (1) How does the value of the buffer between the OFL and the TAC influence fisheries management performance for red grouper? (2) How do TAC strategies for red grouper perform in the presence of episodic events of natural mortality? and (3) Is there a benefit to updating the TAC of red grouper more frequently in a context of episodic events of natural mortality?

Currently, no completed MSE framework is available in the GOM. Since a decision rule is needed for the OSMOSE MSE framework, we decided to use the "broken-stick harvest control rule" that is shown in Fig. 2, which a decision rule that is commonly employed in single-species MSE frameworks (A'mar et al., 2010; Ianelli et al., 2011; Punt et al., 2012; Moffitt et al., 2015). We fixed SSB_{crit} to 0.05*SSB_{msy} following A'mar et al. (2010) and Dorn et al. (2001) (Fig. 2). Thus, the broken-stick harvest control rule for red grouper prescribes that:

$$\begin{cases} OFL = 0 \quad if\ SSB < SSB_{crit} \\ OFL = MSY\dfrac{SSB}{SSB_{msy}} \quad if\ SSB_{crit} \le SSB < SSB_{msy} \\ OFL = MSY \quad if\ SSB \ge SSB_{msy} \end{cases} \tag{1}$$

The TAC of GOM red grouper is determined from the OFL using a method called the "P* approach" (Caddy and McGarvey, 1996; Prager et al., 2003; Shertzer et al., 2008; Prager and Shertzer, 2010; Ralston et al., 2011; Punt et al., 2012; Gulf of Mexico Fishery Management Council, 2014). P* is the acceptable probability that the TAC (referred to as "acceptable biological catch" or "ABC" in the U.S.) exceeds the OFL, which corresponds to the risk of overfishing considered acceptable in the OSMOSE MSE framework (Fig. 1). Fig. 4a summarizes the relationship between the OFL and the ABC under the assumption that the OFL is lognormally distributed with the standard error of the log given by σ_{OFL}. The buffer between OFL and ABC is equal to zero when P* is set to 0.5, and is larger for lower values of P* and higher values for σ_{OFL} (Fig. 4a) (Ralston et al., 2011; Punt et al., 2012). Fig. 4b displays how, given the distribution of the OFL (governed by the value of σ_{OFL}), ABC is determined so that the probability of ABC exceeding OFL is equal to P* (Prager and Shertzer, 2010).

To address Question 1 mentioned above, i.e., "How does the value of the buffer between the OFL and the TAC influence fisheries management performance for red grouper?", we ran simulations with the MSE framework over a 30-year period for three different values of P* (0.3, 0.4, and 0.5; because the GMFMC's SSCs currently assume a P* of 0.4) and a σ_{OFL} fixed to 0.36 (following the recommendations of the GMFMC's SSCs; Gulf of Mexico Fishery Management Council, 2014). Therefore, we ran simulations with the MSE framework for the following buffer values: 0.17, 0.09 and 0. It can be noted in Fig. 4a that different combinations of P* and σ_{OFL} can yield the same buffer value. We made the assumption that the TAC of red grouper is updated every three years, as is planned for future red grouper stock assessments (Gulf of Mexico Fishery Management Council, 2014).

To address Question 2, i.e., "How do TAC strategies for red grouper perform in the presence of episodic events of natural mortality?", we ran simulations with the MSE framework over a 30-year period in the presence or absence of episodic events of natural mortality (*M*), under the assumptions that: (1) P* is equal to 0.3, 0.4, or 0.5; (2) σ_{OFL} is equal to 0.36; and (3) the TAC of red grouper is updated every three years. We defined a simple scenario of episodic events of *M*, where the $M_{diverse}$ of red grouper is increased by a factor of 16 during the last six months of a year characterized by episodic events of *M* (Fig. 5). This scenario is not meant to reflect what is likely to happen on the West Florida Shelf in the near future, but rather to evaluate the performance of TAC strategies in the presence of episodic natural events whose magnitude and frequency were determined to significantly affect red grouper biomass in the OSMOSE MSE framework through preliminary test simulations. The timing of episodic events of *M* (happening during the last six months of given years) was chosen because severe red tide events generally occur during the second half of the year in the GOM (Gulf of Mexico Fishery Management Council, 2014; Driggers et al., 2016).

Finally, to address Question 3, i.e., "Is there a benefit to updating the TAC of red grouper more frequently in a context of episodic events of natural mortality?", we ran simulations with the MSE framework over a 30-year period under the assumptions that P* is equal to 0.3, 0.4, or 0.5, σ_{OFL} is equal to 0.36, and episodic events of *M* occur (as depicted in Fig. 5), under the following four scenarios: (1) the TAC of red grouper is updated every three years (baseline situation); (2) the TAC of red grouper is updated every year; (3) the TAC of red grouper is updated every five years; and (4) the TAC of red grouper is updated every three years and every year following an episodic event of *M*, i.e., a "reactive TAC strategy" is implemented.

Prior to performing all simulations, OSMOSE-WFS was run for 114 years to reach a steady-state (Grüss et al., 2016, 2015). One hundred simulations were performed for each of the combinations of parameters and scenarios mentioned above (e.g., 300 simulations to address Question 1). We assumed no observation error and no implementation error (i.e., the parameters μ_{survey}, σ_{survey}, μ_{imp} and σ_{imp} were all set to zero) for all the simulations we conducted. Assuming no observation error and no implementation error reduces stochasticity in our simulations to stochasticity in the OSMOSE modeling platform. This setting, along with the fact that we performed one hundred simulations for each of the combinations of parameters and scenarios, facilitates the comparison of the outcomes obtained for different combinations of parameters and/or under different scenarios.

To analyze MSE outcomes, we evaluated the following eight performance metrics: (1) the probability that red grouper is not being overfished; (2) the probability that red grouper is not undergoing stock collapse; (3) the net present value (NPV) of discounted revenues from red grouper catch; (4) the stability of red grouper catch; (5) the mean biomass of large predators other than red grouper ("other large predators"); (6) the mean biomass of forage fish and invertebrates (hereafter simply referred to as "forage fish"); (7) the mean catch of other large predators; and (8) the mean catch of forage fish. Higher values are targeted for each of the eight performance metrics. We assessed each performance metric under a short-term perspective (considering the first 10 years of simulations), a medium-term perspective (considering the first 20 years of simulations), and a long-term perspective (considering the 30 years of simulations). Regarding the long-term perspective, note that integrating results over the full time series brings more variability than averaging results over the last years of simulations.

The probability that red grouper is not being overfished was evaluated because the GMFMC's Reef Fish Management Plan requires fish stocks to be rebuilt whenever they are declining. This performance metric was calculated by determining the probability that the SSB of red grouper is above its SSB_{msy} over the period under consideration (i.e., the first 10 or 20 years of simulations or the 30 years of simulations, depending on whether a short-term, a medium-term or a long-term perspective is adopted, respectively).

The probability that red grouper is not undergoing stock collapse was assessed because the GMFMC's Reef Fish Management Plan states that the risk of collapse of red grouper, defined as the probability that SSB is lower than $SSB_{20\%SPR}$ (the SSB at which SSBR is at 20% of its unfished value), should be avoided. Therefore, we calculated the probability that red grouper is not undergoing stock collapse as the probability that the SSB of red grouper is above its $SSB_{20\%SPR}$ over the period under consideration.

We estimated the NPV of discounted revenues from red grouper catch from a short-term, a medium-term and a long-term perspective, because the GMFMC's Reef Fish Management Plan encourages the maximization of net economic benefits from the reef fish fisheries of the GOM. The NPV of discounted revenues from red grouper catch (in U.S. dollars, \$) is given by (Punt et al., 2012):

$$NPV = \sum_{y} \frac{pC_y}{(1+r)^{y+1}} \tag{2}$$

where p is the ex-vessel price per ton of red grouper catch (in \$); C_y is red grouper catch in tons in year y; and r is the discount rate. To calculate p, we assumed an ex-vessel price per ton of red grouper catch of \$3, based on http://www.nationalfisherman.com/november-2013/2337-market-reports. Discount rates of 0.028, 0.031 and 0.034 were used following U.S. Office of Management and Budget Guidance (OMB, 2015) to reflect the economic effects of time preference over the short-term, medium-term and long-term, respectively.

We evaluated the stability of red grouper catch, because inter-annual variability of fisheries catches is a concern for fisheries managers and fishing industry representatives that is typically taken into account in the MSE process (A'mar et al., 2010; Punt, 2011; Punt et al., 2014; Tong et al., 2014; Schirripa, 2015). We calculated the stability of red grouper catch as the inverse of the coefficient of variation of red grouper catch over the period under consideration.

Finally, we assessed the mean biomasses and mean catches of other predators and forage fish, because other large predators have a high economic value and forage fish are the essential food source of large predators and charismatic animals not explicitly considered in OSMOSE-WFS (e.g., marine mammals and seabirds). It is therefore desirable to keep the biomasses and catches of other predators and forage fish at the highest levels possible when red grouper is allowed to rebuild through a TAC strategy.

The eight performance metrics were displayed in the form of boxplots (Dichmont et al., 2008; Punt et al., 2014), and their medians were shown on a radial graph. Radial graphs are figures classically used to communicate MSE results to fisheries managers and other stakeholders for their ease of visualization (Fulton et al. 2014; Punt et al., 2014). Before being displayed on radial graphs, the median estimates of six performance metrics, namely the NPV of discounted revenues from red grouper catch, the stability of red grouper catch, and the mean biomasses and catches of other large predators and forage fish, were standardized to their maximum values across a range of scenarios. This transformation ensured that the value of the six performance metrics ranged between 0 and 1 on the radial graphs, where 0 reflects poor performance and 1 reflects good performance (Fulton et al. 2014). To enable the visualization and comparison of the outcomes of the simulations run to address Questions 1 and 2 in the same figure, the medians of the six performance metrics were normalized over all P* values, all perspectives (i.e., short-term, medium-term, and long-term) and all environmental contexts (i.e., presence or absence of episodic events of *M*). To visualize the outcomes of the simulations run to address Question 3, the medians of the six performance metrics were normalized over all P* values, all perspectives and all TAC update scenarios (i.e., red grouper TAC updated every year, every three years, every five years, or every three years and every year following an episodic event of *M*).

Moreover, a composite performance index was computed as the sum of the eight performance metrics (standardized in the case of the NPV of discounted revenues from red grouper catch, the stability of red grouper catch, and the mean biomasses and catches of other large predators and forage fish). The purpose of this composite index is to try to identify, among a set of TAC strategies, the one that performs best (Ianelli et al., 2011).

3. Results

3.1. Reference points

An equilibrium catch curve (i.e., fisheries catches at equilibrium as a function of annual fishing mortality rate), as well as SSB and SPR at equilibrium as a function of annual fishing mortality rate, were constructed for red grouper using OSMOSE-WFS (Fig. 6). From the equilibrium catch curve, the F_{msy} and MSY of red grouper were estimated to be 0.13 year^{-1} and 4,482 tons, respectively (Fig. 6a). Given that the annual fishing mortality of red grouper in the baseline (current) configuration of OSMOSE-WFS ($F_{current}$) is equal to 0.22 year^{-1} (Appendix D), then OSMOSE-WFS predicts that $F_{current}$ / F_{msy} = 1.69 for red grouper, i.e., that GOM red grouper was experiencing overfishing in the 2000s. From the curve giving SSB as a function of annual fishing mortality rate, the SSB_{msy} of red grouper was determined to be equal to 28,225 tons (Fig. 6b).

The annual fishing mortality rate at which SPR reaches 20%, $F_{20\%SPR}$, was estimated to be 0.22 year^{-1} (Fig. 6c). From the curve giving SSB as a function of annual fishing mortality rate, we determined that the SSB of red grouper at 20% SPR, $SSB_{20\%SPR}$, is equal to 13,139 tons (Fig. 6b).

3.2. Impacts of the buffer on the performance of TAC strategies

Red grouper catch is initially decreased and then gradually increases over time, for all P* values, i.e., for all values of the buffer between the OFL and the ABC (Fig. 7a). Usually, the higher the P* value (i.e., the lower the buffer value), the higher the red grouper catch. Red grouper catch is initially decreased by 37% when P* is set to 0.5 (i.e., when the buffer equals 0), by 42% when P* is set to 0.4 (i.e., when the buffer equals 0.09), and by 48% when P* is set to 0.3 (i.e., when the buffer equals 0.17). Red grouper catch exceeds its initial level after 10 years of simulations, for all P* values. It plateaus at 1.35 times its initial level starting from year 22 when P* = 0.5, at 1.23 times its initial level starting from year 19 when P* = 0.4, and at 1.12 times its initial level starting from year 13 when P* = 0.3 (Fig. 7a).

Red grouper biomass increases substantially over time, for all P* values (Fig. 8a). The lower the P* value, the higher the red grouper biomass. At the end of simulations, red grouper biomass reaches 2.45 times its initial level when P* is set to 0.5, 2.75 times its initial level when P* is set to 0.4, and 3.36 times its initial level when P* is set to 0.3 (Fig. 8a).

Red grouper fishing mortality rate decreases substantially at the beginning of simulations, when OSMOSE-WFS starts communicating with the MP, for all P* values (Fig. 9a). Then, until the middle of the period of simulations, red grouper fishing mortality rate fluctuates around 0.98 times F_{msy} when P* = 0.5, 0.84 times F_{msy} when P* = 0.4, and 0.77 times F_{msy} when P* = 0.3, before decreasing (Fig. 9a).

The biomass and catch of other large predators initially increase slightly and then decrease for all P* values (Figs. 7b and 8b). The lower the P* value, the lower the biomass and catch levels of other large predators at the end of simulations (Figs. 7b and 8b).

The biomass and catch of small predators and forage fish are relatively insensitive to changes in red grouper biomass and the value of P* (Figs. 7c-d and 8c-d). The biomass and catch of small predators tend to diminish slightly over time, except when P* is equal to 0.5, where they initially increase slightly before decreasing slightly (Figs. 7c and 8c). Moreover, changes in red grouper biomass and the value of P* have virtually no impact on the biomass and catch of forage fish (Figs. 7d and 8d).

Performance metrics indicate that, the lower the P* value, the higher the probabilities that red grouper is not being overfished and that red grouper is not undergoing stock collapse (Figs. 10a-b and 11a-c). Conversely, the lower the P* value, the smaller the median value of NPV of discounted revenues from red grouper catch and the smaller the stability of red grouper catch (Figs. 10c-d and 11a-c). However, differences in terms of NPV of discounted revenues from red grouper catch and stability of red grouper catch are relatively small from one P* value to another (Figs. 10c-d and 11a-c). NPV of discounted revenues from red grouper catch are low under a short-term perspective, and are slightly higher under a medium-term than under a long-term perspective (Fig. 10c). Finally, there are virtually no differences between the median biomasses and catches of other large predators and forage fish predicted for the different P* values (Figs. 11a-c).

The highest composite performance index was obtained for the smallest P* value (i.e., 0.3), under the medium-term and long-term perspectives, but not under the short-term perspective where a P* of 0.3 resulted in the smallest composite performance index (Table 2). This result is due to the fact that, under the short-term perspective, setting P* to 0.3 leads to a lower stability of red grouper catch than setting P* to a higher value (Fig. 11a). The composite performance indices computed for P* = 0.4 and P* = 0.5 are similar under the medium-term and long-term perspectives. This primarily stems from the fact that, under the medium-term and long-term perspectives, differences between the probability that red grouper is not being overfished predicted when P* = 0.3 and that predicted when P* = 0.5 are large, while differences between the probability that red grouper is not being overfished predicted when P* = 0.4 and that predicted when P* = 0.5 are relatively small (Figs. 11a-c).

3.3. Performance of TAC strategies in the presence of episodic events of natural mortality

Red grouper biomass is lower in the presence of episodic events of *M*, for all P* values (Figs. 8e vs 8a). The occurrence of episodic events of *M* is followed by temporary decreases in red grouper biomass (Fig. 8e). Red grouper biomass at the end of simulations is 18%, 14% and 15% lower in the presence of episodic events of *M*, when P* is set to 0.3, 0.4 and 0.5, respectively.

Episodic events of *M* have a negative impact on red grouper catch for all P* values (Figs. 7e vs 7a). Red grouper catch exceeds its initial level after 16 years of simulations in the presence of episodic events of *M*, whereas this occurred after 10 years of simulation in the absence of episodic events of *M*. Moreover, red grouper catch reaches a plateau later in the presence of episodic events of *M*. Also, when P* is equal to 0.5 (i.e., when the buffer equals 0), red grouper plateaus at 1.19 times its initial level in the presence of episodic events of *M* vs.1.35 times its initial level in the absence of episodic events of *M* (Figs. 7e vs. 7a).

Red grouper fishing mortality rate is higher in the presence of episodic events of *M*, for all P* values (Figs. 9b vs 9a). In particular, when episodic events of *M* occur and P* is set to 0.5, red grouper fishing mortality rate fluctuates around F_{msy} during the 30 years of simulation to reach 0.96*F_{msy} at the end of simulations (Fig. 9b).

Episodic events of *M*, which affect only red grouper in our simulations, tend to have a positive impact on the biomass and catch of the other HTL groups represented in the OSMOSE-WFS model, for all P* values (Figs. 7f-h vs. 7b-d and 8f-h vs. 8b-d). Declines in the biomass and catch of other large predators are less pronounced in the presence of episodic events of *M* (Figs. 7f and 8f). The biomass and catch of small predators remain above their initial levels in the presence of episodic events of *M*, while they tend to decrease slightly in the absence of episodic events of *M* (Figs. 7g vs. 7c and 8g vs. 8c). The biomass and catch of forage fish are virtually insensitive to changes in red grouper biomass both when episodic events of *M* are present or absent (Figs. 7d and h and 8d and h).

The occurrence of episodic events of *M* does not have a large impact on performance metrics (Figs. 10 and 11). The noticeable differences between the scenarios where episodic events of *M* occur and those where episodic events of *M* do not occur are that, for all P* values: (1) the probability that red grouper is not being overfished strongly decreases in the presence of episodic events of *M* (Figs. 10e vs. 10a); (2) the NPV of discounted revenues from red grouper catch decreases slightly in the presence of episodic events of *M* (Figs 10g vs. 10c); and (3) the stability of red grouper catch increases slightly in the presence of episodic events of *M* for P* = 0.4 (Figs. 10h vs. 10d).

In the presence of episodic events of *M*, the highest composite performance index was obtained for P* = 0.5 under the short-term perspective, and for P* = 0.4 under the medium-term and long-term perspectives (Table 2). This result essentially stems from the fact that the NPV of discounted revenues from red grouper catch and the stability of red grouper catch are higher when P* is set to 0.4 or 0.5 than when it is set to 0.3 (Figs. 11d-f). However, the differences between the composite performance indices computed for P* = 0.3 and P* = 0.4 are very small under the medium-term and long-term perspectives (Table 2), because of the stronger positive impact of P* = 0.3 on the probability that red grouper is not being overfished (Figs. 11e-f).

3.4. Impacts of the frequency of TAC updates in a context of episodic events of natural mortality

The frequency of TAC updates has a limited impact on the biomass, catch and fishing mortality rate of red grouper in a context of episodic events of *M* (Figs. 12 and 13). During the 30 years of simulation, updating red grouper TAC every year generally leads to higher red grouper catch than updating red grouper catch every 3 years, while updating red grouper TAC every 5 years generally results in lower red grouper catch (Figs. 12a-c). Moreover, the "reactive TAC strategy" consisting of updating red grouper TAC every 3 years and every year following an episodic event of *M* general leads to lower red grouper catch than the strategy consisting of updating red grouper TAC every 3 years only. However, differences are minute from one TAC update scenario to another (Figs. 12a-c). Red grouper biomass levels are similar from one TAC update scenario to another, although the lowest red grouper biomass levels are generally obtained when the reactive TAC strategy is implemented (Figs. 12d-f).

The decline in the biomass and catch of other large predators that accompanies changes in red grouper biomass is less pronounced when red grouper TAC is updated every year than when it is updated every three years, and more pronounced when it is updated every 5 years (Fig. E). Yet, differences are small from one TAC update scenario to another. Moreover, the frequency of TAC updates in a context of episodic events of *M* does not affect the biomass and catch of small predators and forage fish (Figs F and G).

Overall, the frequency of TAC updates does not have a large impact on performance metrics (Figs. 14 and H, I, J and K). The only noticeable - but very small - differences between TAC update scenarios are that: (1) the highest NPV of discounted revenues from red grouper catch and stability of the catch are usually obtained when red grouper TAC is updated every year; and (2) these two performance metrics are usually larger when the reactive TAC strategy is implemented than when red grouper TAC is updated every 3 years or every 5 years (Figs. 14 and H). In general, the TAC strategy consisting of updating red grouper TAC every year has the highest composite performance index, followed by the reactive TAC strategy, regardless of the value of P* and the perspective adopted (i.e., short-term, medium-term or long-term) (Table 3).

4. Discussion

In the present study, we introduced the MSE framework designed for the OSMOSE modeling platform. This MSE framework is relatively simple and currently does not include an assessment model. We applied this MSE framework to the OSMOSE-WFS model for red grouper, as a first test case study. The MSE conducted for red grouper must be considered preliminary and strategic (*sensu* Plaganyi (2007) and Fulton (2010)); it intends to provide broad, qualitative insights into the potential impacts of a few TAC strategies implemented for red grouper, under a very specific set of assumptions (Butterworth and Punt, 1999; Kraak et al., 2008, 2010; Fulton et al., 2014; Punt et al., 2014). Below, we discuss the findings gleaned from applying the OSMOSE MSE framework to red grouper and how future research could provide more insights into the possible impacts of TAC strategies for the species. Then, we give a few perspectives for the OSMOSE MSE framework.

4.1. Application of the OSMOSE MSE framework to red grouper

The equilibrium catch curve of GOM red grouper constructed with OSMOSE-WFS indicates that the fish population was undergoing overfishing in the 2000s from an ecosystem perspective. This result is in agreement with Grüss et al. (2016), while the 2009 stock assessment of GOM red grouper suggests that the fish population was experiencing overfishing until 2005 (SEDAR, 2009) and the 2015 assessment suggests that the fish population was not undergoing overfishing in the 2000s, except in 2005 (although this last result is an artifact due to the fact that red tide was treated as a pseudo-fishing fleet in the assessment model) (SEDAR 42, 2015). Thus, the MSE framework applied to red grouper starts from a steady state where red grouper is undergoing overfishing. Consequently, red grouper catch is initially decreased when OSMOSE-WFS communicates with the MP. Moreover, we determined that the annual fishing mortality rate of red grouper before OSMOSE-WFS starts communicating with the MP is equal to the annual fishing mortality rate at which red grouper SPR reaches 20%. Therefore, the MSE framework applied to red grouper also starts from a steady state where red grouper is at risk of collapse. Finally, red grouper SSB before OSMOSE-WFS starts communicating with the MP was much higher than the critical level of SSB below which no fishing should occur (i.e., SSB_{crit}); Also, red grouper SSB never fell below SSB_{crit} when OSMOSE-WFS was communicating with the MP, under all scenarios, even in the presence of episodic events of M. Therefore, the ABC of red grouper dictated by the MP was always greater than zero under all the scenarios considered in the present study.

The MSE simulations conducted in the present study indicate that, after initially decreasing, red grouper catch gradually builds up, for all P* values, i.e., for all buffer values between the OFL and the ABC. Initial decreases in red grouper catch, which are significant (37 to 48%), enable red grouper biomass to substantially rebuild and red grouper catch to exceed its initial level in the medium term (i.e., after 10 to 20 years of simulations). We found that, the higher the P* value, i.e. the lower the buffer between the OFL and the ABC, the lower the initial reduction in red grouper catch. Furthermore, the higher the P* value, the larger the red grouper catch, the higher the NPV of discounted revenues from red grouper catch, and the more stable the red grouper catch. Thus, larger P* values result in higher catch-related metrics for red grouper. By contrast, the lower the P* value, the larger the red grouper biomass and the probability that red grouper is not being overfished. Thus, smaller P* values result in higher biomass-related metrics for red grouper, and the choice of a buffer value and, therefore, precautionary fisheries management, imposes a trade-off between biomass-related and catch-related metrics for red grouper. These results concur with those of previous MSE studies (Shertzer et al., 2008, 2010; Punt et al., 2012).

As in Grüss et al. (2016), we found that modifications in the fishing mortality of red grouper are accompanied by significant changes in the biomass and catch of other large predators, due to competition for food and predation by red grouper upon the juveniles of other large predators. On the other hand, the biomass and catch of forage fish, which are the major prey of all large predators, do not vary to any significant degree when the fishing mortality of red grouper is altered (Grüss et al., 2016). The absence of trophic cascade in response to changes in red grouper fishing mortality stems from the high complexity and high redundancy of the system modeled in OSMOSE-WFS (Grüss et al., 2016). Observations for other large predators and forage fish apply regardless of the occurrence or absence of episodic events of *M* and of how frequently the TAC of red grouper is updated.

The performance of the TAC strategies for red grouper for different P* values (different buffer values) was evaluated through eight performance metrics and a composite performance index, which is the sum of the eight performance metrics. The four performance metrics related to other species (i.e., the mean biomasses and catches of other large predators and forage fish) did not vary significantly from one buffer value to another, nor in the presence vs. absence of episodic events of *M* and from one TAC update scenario to another. The P* value associated with the highest composite performance index depended on the occurrence or absence of episodic events of *M* and the perspective adopted (i.e., short-term, medium-term or long-term). Unfortunately, the composite performance index computed in this study cannot be used to identify the best performing TAC strategies, i.e., TAC strategies balancing biomass-related and catch-related outcomes, since, as we saw earlier, the P* value assumed involves a trade-off between biomass-related and catch-related metrics for the species targeted by management efforts.

All the results discussed above consider both the short-term and the medium- and long-terms. However, managers and fishing industry representatives are often concerned with the short-term impacts of fisheries management measures (Kell et al., 2003; Holland, 2010; Punt et al., 2012). The simulated NPV of discounted revenues suggest that adopting TAC strategies using a simple "broken-stick harvest control rule" entails substantial losses in fisheries revenues in the short term (Figs. 10c and g and 14c, g and k). Even if these short-term losses were compensated by large increases in revenues in the medium- to long-term, managers and fishing industry representatives may still gauge TAC strategies based primarily on their short-term impacts on fisheries. Therefore, it would be useful to run additional simulations for red grouper comparing the short-term fisheries effects of TAC strategies involving different decision rules (see the next subsections).

Episodic events of *M* reduced the biomass of red grouper and significantly increased the probability of red grouper being overfished, as well as the probability of red grouper undergoing overfishing (Figs. 9b and 13), for all buffer values. This result suggests that, in the face of potential episodic *M* additional to baseline natural mortality, the GMFMC's SSCs should employ a greater buffer between the OFL and the ABC, so as to ensure that the probability of red grouper not undergoing overfishing remains at its expected level. Episodic events of *M* also had a negative impact on red grouper catch and the NPV of discounted revenues from red grouper catch. However, these events had a slightly positive effect on the stability of red grouper catch. This last result stems from the fact that episodic events of *M* decrease the SSB of red grouper to a level that leads the MP to prescribe a TAC for red grouper lower than would have been prescribed in the absence of episodic events (Figs. 7e vs. 7a).

The frequency of TAC updates in a context of episodic events of *M* was found to have a non-significant impact on biomass-related and catch-related metrics for red grouper and was not affected by the buffer value. In general, updating red grouper TAC every year or a reactive TAC strategy consisting of updating the TAC of red grouper every three years and after every episodic event of *M* resulted in higher red grouper catch, NPV of discounted revenues and/or red grouper catch stability compared to updating the TAC of red grouper every three years or every five years. However, differences between TAC update scenarios are small. Moreover, increasing the frequency of TAC updates would entail significant costs in the real world. Therefore, our results suggest that there is no benefit in increasing the frequency of TAC updates for GOM red grouper. These results concur with those of Kell et al. (2003), who found that the frequency of TAC updates for Atlantic tuna stocks was less important for a successful management strategy than other MSE features, such as the proxy used for MSY.

4.2. Limitations of the MSE conducted for red grouper and perspectives

The MSE carried out here uses a relatively simple MSE framework that does not include an assessment model. Yet, based on the outcomes of previous MSE studies (Kell et al., 2003; Shertzer et al., 2008, 2010; Punt et al., 2012), we suspect that future MSE simulations should not alter the main findings of the present study, i.e., that: (1) in the face of potential episodic *M* (in addition to baseline natural mortality), the GMFMC's SSCs should employ a greater buffer between the OFL and the ABC, so as to ensure that the probability of red grouper not undergoing overfishing remains at its expected level; and (2) updating red grouper TAC more frequently than every three years in a context of environmental changes may not have a large impact on biomass-related and catch-related metrics for red grouper. The limitations of the MSE conducted in the present study include: (1) a simplification of the process establishing a TAC for GOM red grouper; (2) the exploration of a limited number of management and environmental scenarios; (3) the lack of significant differences in the value of several performance metrics from one scenario to another; and (4) the representation in the OSMOSE-WFS model of dynamics on the West Florida Shelf for the 2000s, which may have changed since then.

The determination of TACs and OFLs in the U.S. is more complex than simulated in the OSMOSE MSE framework (MSRA, 2006; Federal Register, 2008; Holland, 2010). First, in the U.S., the TAC is an acceptable catch limit (ACL), which takes into account both scientific and implementation uncertainties, as opposed to an ABC, which considers only scientific uncertainty (Caddy and Mahon, 1995; Prager and Shertzer, 2010; Shertzer et al., 2010). The SSCs determine an ABC from the OFL based on P* and other factors, and then the Fishery Council decides upon an ACL based on the acceptable probability P** that the ACL will exceed the ABC (Shertzer et al., 2010). Some authors (Prager and Shertzer, 2010; Shertzer et al., 2010) suggest the use of the acceptable probability that the ACL will exceed the OFL, P***, to directly transition from the OFL to the ACL. The OSMOSE MSE framework could easily prescribe an ACL from the OFL based on P***, which would basically be P* increased to account for implementation uncertainty (Prager and Shertzer, 2010; Shertzer et al., 2010). Second, the estimation of an OFL for an assessed U.S. fish population is more sophisticated than what is currently implemented in the OSMOSE MSE framework (Holland, 2010; Punt, 2011). This estimation is carried out in two steps. The first step involves an assessment of the fish population to determine its status. The second step consists of defining F_{lim} based on the status of the fish population. If the fish population is not overfished, then F_{lim} is the F_{msy} of the population or a proxy of it; otherwise, simulations are conducted to determine a value for F_{lim} which would allow the population to rebuild over a certain time frame (Holland, 2010; Punt, 2011). The computations of these two steps within the MP coupled to OSMOSE could be implemented by integrating an assessment model within the MP (see the next subsection).

In this study, we carried out an MSE for red grouper under a limited number of management and environmental scenarios, since the primary intentions of the present paper were to introduce the OSMOSE MSE framework and to test this framework for the first time. First, only one scenario of episodic events of M thought to affect red grouper biomass was considered; it would be informative to evaluate TAC strategies for red grouper under contrasting scenarios of how environmental events affect the species. It was assumed in the present study that episodic M is additional to any baseline natural mortality, which is certainly the case with most anthropogenic mortality events. However, it is possible that species adapted to naturally occurring episodic mortality events may have higher productivity and hence the assumption of simply additive natural mortality may not be correct. Research is ongoing as to whether red grouper is adapted to episodic events of M due to red tides, which should be taken into consideration in future studies conducting MSE for red grouper. Furthermore, in the present study, for simplicity, episodic events of M were assumed to have an effect on red grouper only, although many other functional groups of the West Florida Shelf are likely to be affected by such events (Gray, 2014; Sagarese et al., 2015; Driggers et al., 2016); future MSE runs for red grouper should take this possibility into account and assess how this impacts MSE outcomes. Also, only one decision rule, the broken-stick harvest control rule, was implemented in the MP developed for the present study; further discussions with the GMFMC's SSCs will be useful to determine which additional decision rules could be integrated into the OSMOSE MSE framework for red grouper. Finally, only three buffer values (0.17, 0.09, and 0) were considered in the present paper, assuming that P* is equal to 0.3, 0.4 or 0.5, and that σ_{OFL} equals 0.36 (following the recommendations of Ralston et al. (2011)). A MSE should be conducted for red grouper for other buffer values, especially under the assumption that σ_{OFL} may be greater than 0.36. The use of a σ_{OFL} greater than 0.36 may be relevant, because Ralston et al. (2011)'s methodology for estimating σ_{OFL} ignores some of the components of scientific uncertainty, including forecast uncertainty and uncertainty in computing optimal harvest rates.

The value of some of the performance metrics often did not differ significantly from one scenario to another in the present study. In particular, the mean biomasses and fisheries catches of other large predators and forage fish showed very limited variation between the different scenarios. Thus, the composite performance index developed in the present study cannot reliably discriminate between “high” and ”low” performing TAC strategies. The eight performance metrics considered in the presence study were selected based on the concerns of fisheries managers and other stakeholders; further discussions with stakeholders and test simulations are needed to identify other performance metrics that may show more contrast from one scenario to another.

The current OSMOSE-WFS model simulates dynamics on the West Florida Shelf in the 2000s. The MSE conducted for GOM red grouper in this study starts from a steady-state where the fish population is experiencing overfishing, while the 2015 stock assessment of GOM red grouper suggests that the fish population has not been undergoing overfishing since 1996, except in 2005 (SEDAR 42, 2015). The 2015 assessment of GOM red grouper also suggests that the fish population is not undergoing overfishing in the 2010s (SEDAR 42, 2015). Therefore, it would be advantageous to update OSMOSE-WFS so that the model represents dynamics of the West Florida Shelf in the 2010s, and then run MSE for red grouper with this updated model to assess how TAC strategies perform in a system that better reflects current conditions in the West Florida Shelf ecosystem.

4.3. Perspectives for the OSMOSE MSE framework

The creation of an MSE framework for OSMOSE enabled the implementation of two-way interactions between HTL groups and fisheries managers in the modeling platform, which were previously missing. Thus, through the development of an MSE framework, the end-to end modeling approach OSMOSE is now better able to provide advice for EBFM. MSE has long been integrated into the Atlantis end-to-end modeling platform (Fulton et al., 2007, 2011, 2014). Moreover, a MSE module is currently being developed and tested for the EwE modeling platform, which establishes fishing effort levels based on TACs derived from harvest control rules (Steenbeek et al., 2016). Therefore, it will soon be possible to conduct multi-model evaluations of fishing management strategies, using OSMOSE, Atlantis and EwE; multi-model MSEs will better evaluate uncertainties around the potential impacts of TACs and other fisheries management measures (Kell et al., 2007; Townsend et al., 2014).

The current OSMOSE MSE framework accounts for uncertainty in stock assessments and includes observation and implementation errors. Moreover, because OSMOSE is a stochastic modeling approach, the natural variability of the system modeled in an OSMOSE model can be quite high, as illustrated by the boxplots presented in the present study (Figs. 10, 14 and H). To account for the quite high natural variability in OSMOSE and be able to discuss the results of the OSMOSE MSE framework based on hundreds of simulation, we implemented the OSMOSE MSE framework on a cluster of calculations. Although radial graphs based on median performance measures are the classical figures used to communicate MSE results to fisheries managers and other stakeholders, boxplots should always be produced to report the variability of the results of the OSMOSE MSE framework due to OSMOSE stochasticity. Median time trajectories supplemented with shaded swathes representing percentiles (A’mar et al., 2010; Ianelli et al., 2011; Punt, 2011) would also be desirable in future studies using the OSMOSE MSE framework.

The impacts of the sampling, assessment and implementation processes on the outcomes of the OSMOSE MSE framework should be better understood and represented. In the present study, observation and implementation errors were both set to zero. In future studies, it would be advantageous to investigate the impacts of non-zero observation and implementation errors and of the length of the observation time series considered by the MP on the performance of fisheries management strategies. A number of modifications could also be introduced in the OSMOSE MSE framework, including the incorporation of an assessment model into the MP, and the development of more sophisticated sampling and implementation processes. First, a MP often integrates an assessment model, which determines the status of the fish populations under consideration and, eventually, runs projections to generate an estimate of F_{lim} or OFL (Sainsbury et al., 2000; Kell et al., 2003, 2007; Holland, 2010; Punt, 2011). The use of an assessment model in the OSMOSE MSE framework would entail: (1) making the sampling module communicate with the assessment model, which would then deliver a F_{lim} or an OFL; and (2) estimating reference points for the OSMOSE MSE framework with the assessment model rather than with OSMOSE; reference points in that case should be dynamic and updated within the MSE loop, since natural mortality rates in OSMOSE change over time. Second, the sampling and implementation processes are represented in a very simple way in the current OSMOSE MSE framework through the use of log-normally distributed errors. In the future, it would be interesting to design a sampling module within OSMOSE itself, which would simulate the spatio-temporal dynamics of research surveys. Such an endeavor would enable an evaluation of research monitoring programs (Sainsbury et al., 2000; Holland, 2010). Moreover, fishers could become explicit components of the OSMOSE modeling platform, and the simulation of their behavior could account for implementation uncertainty in lieu of the implementation module of the current OSMOSE MSE framework. The integration of fishers as explicit components of OSMOSE and the simulation of their behavior would also address the issue of the simplistic assumption currently made in OSMOSE that fishing mortality is distributed uniformly over space.

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Supplementary data

Supplementary data associated with this article can be found in the online version of the manuscript.

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Figure captions

Fig. 1. Flowchart of the framework designed to conduct management strategy evaluation (MSE) with the OSMOSE modeling platform. SSB = spawning stock biomass – F = fishing mortality rate – TAC = total allowable catch – Focal functional groups = high trophic level functional groups targeted by management efforts.

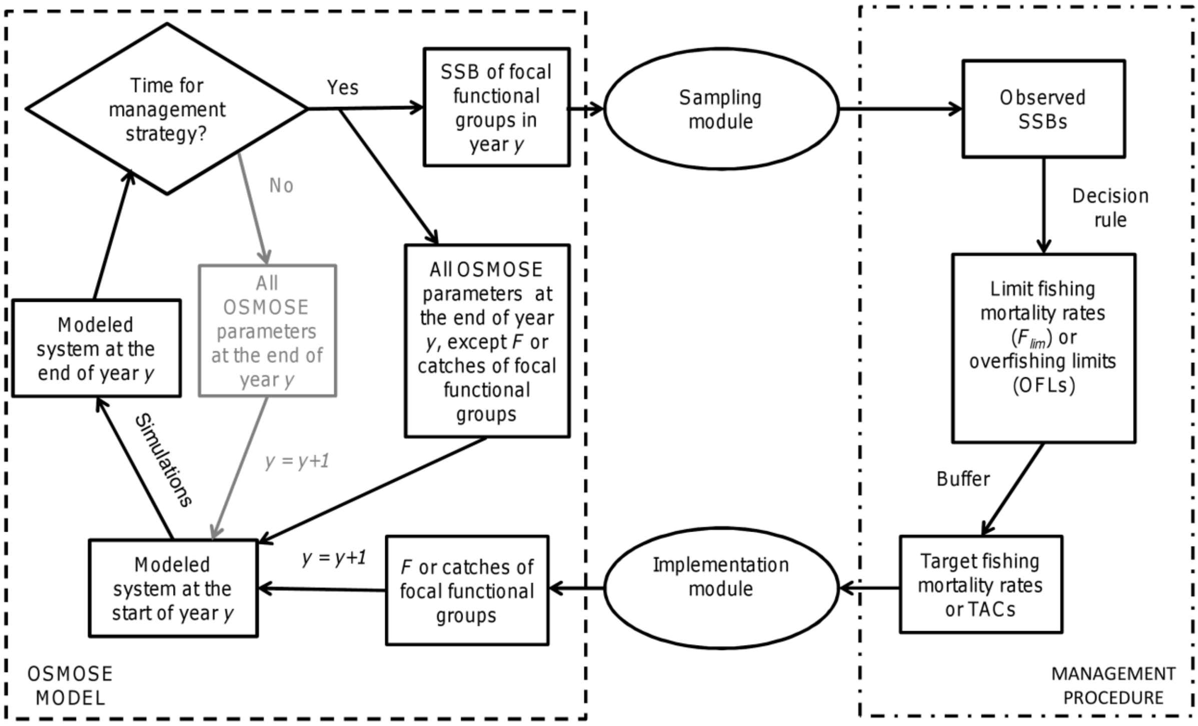

Fig. 2. Example of decision rule implemented in the OSMOSE management strategy evaluation (MSE) framework. The decision rule displayed here is the "broken-stick harvest control rule", which determines a catch limit (overfishing limit or OFL) based on a spawning stock biomass (SSB) level and reference points including: (1) MSY, the maximum sustainable yield (MSY); (2) SSB_{msy}, the SSB at the annual fishing mortality rate resulting in MSY; and (3) SSB_{crit}, the critical level of SSB below which no fishing should occur.

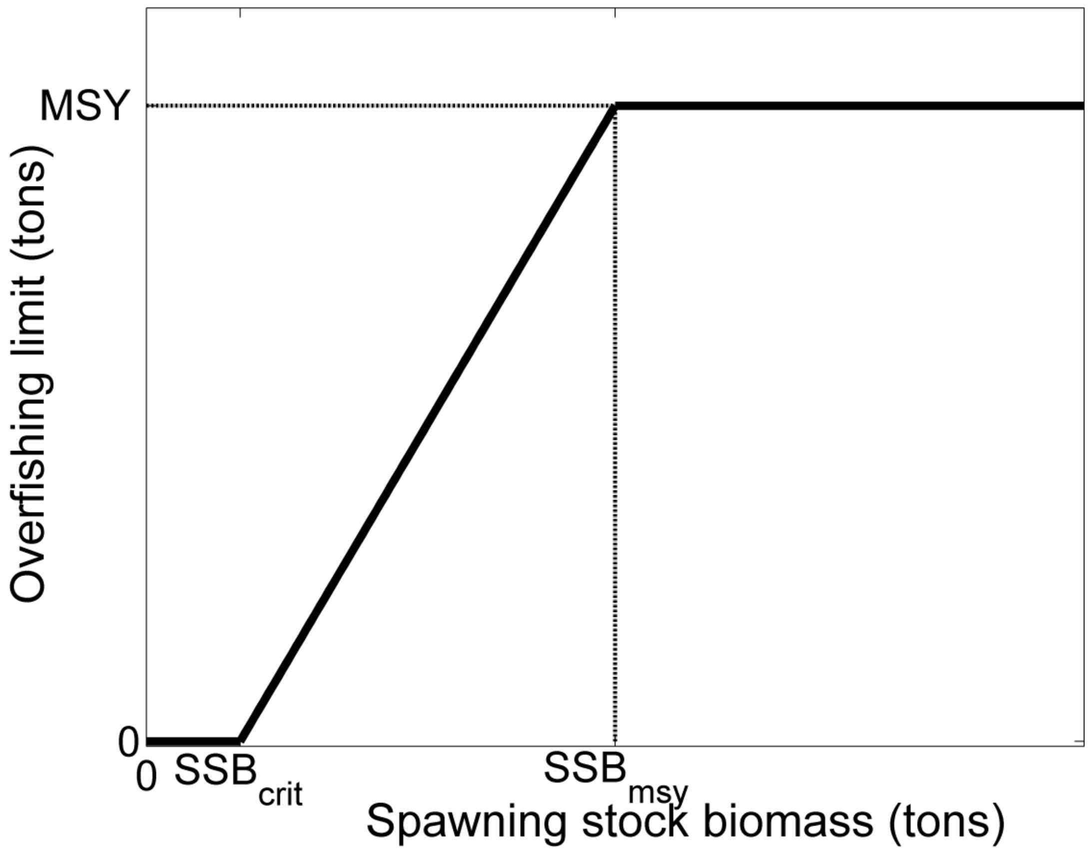

Fig. 3. Map of the West Florida Shelf showing the spatial cells of the OSMOSE-WFS model (filled in dark grey). The spatial domain of OSMOSE-WFS extends from approximately 25.2° N to 31°N in latitude and from approximately 80.2°W to 87°W in longitude and comprises 465 square cells in a grid with closed boundaries.

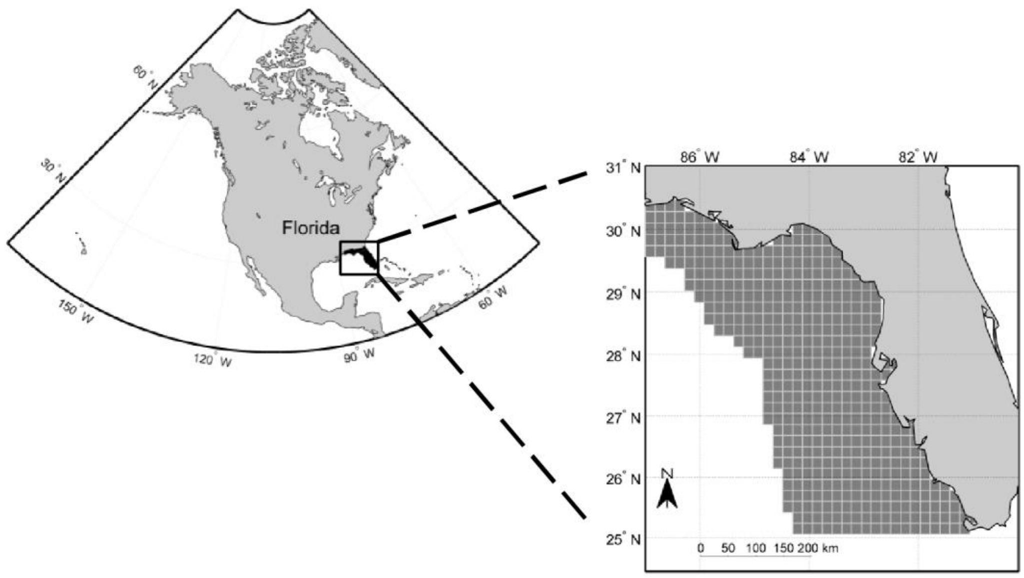

Fig. 4. Method used for setting the acceptable biological catch (ABC) of red grouper (*Epinephelus morio*) from an overfishing limit (OFL) and a buffer. (a) The buffer between the OFL and the ABC is calculated from the probability of overfishing considered acceptable (P*) and the standard error of the log of the distribution of OFL (σ_{OFL}), under the assumption that the OFL is lognormally distributed. **(b)** Given the distribution of OFL governed by σ_{OFL}, ABC is determined so that the probability of ABC exceeding OFL is equal to P*.

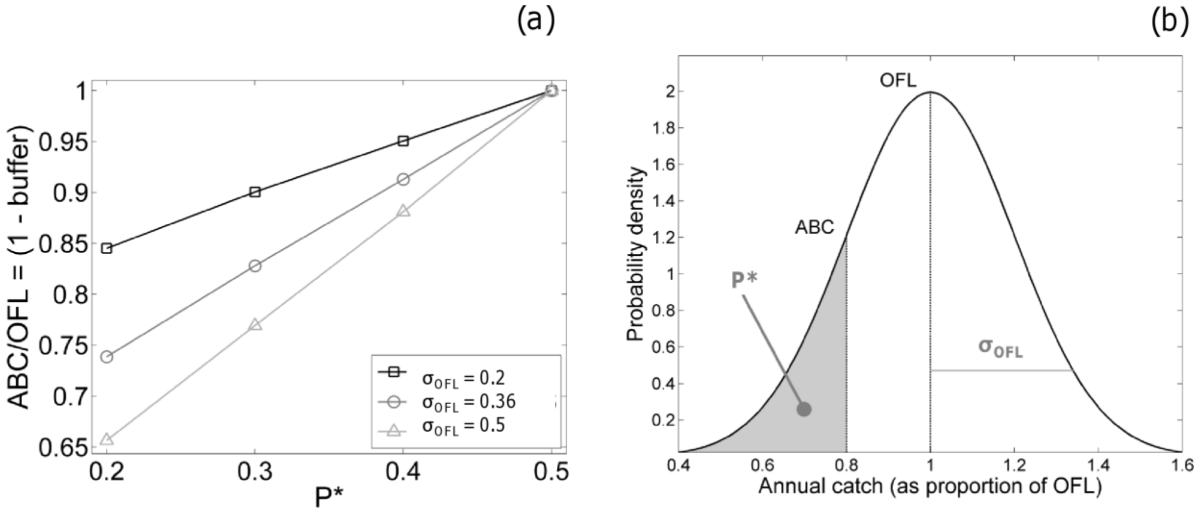

Fig. 5. Scenario of episodic events of natural mortality considered in the present study. This scenario assumes that the natural mortality of red grouper (*Epinephelus morio*) due to causes not represented in the OSMOSE-WFS model ($M_{diverse}$) is increased by a factor of 16 during the last six months of years 5, 8 and 20.

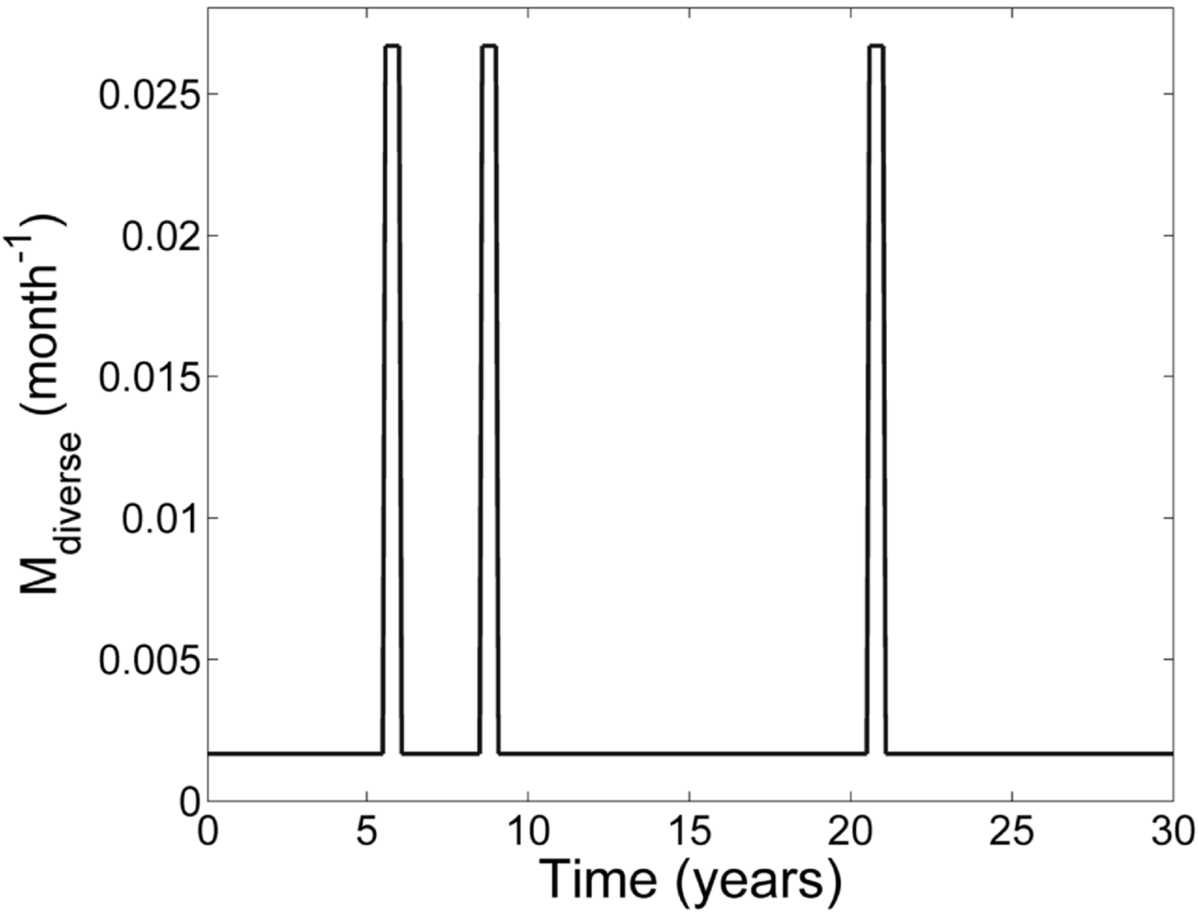

Fig. 6. (a) Fisheries catches, (b) spawning stock biomass and (c) spawning potential ratio at equilibrium as a function of annual fishing mortality rate for red grouper (*Epinephelus morio*), estimated with OSMOSE-WFS. For all panels, the vertical full line indicates the annual fishing mortality rate resulting in the maximum sustainable yield of red grouper (F_{msy}), while the vertical dotted line indicates the annual fishing mortality rate at which the spawning potential ratio of red grouper reaches 20% ($F_{20\%SPR}$).

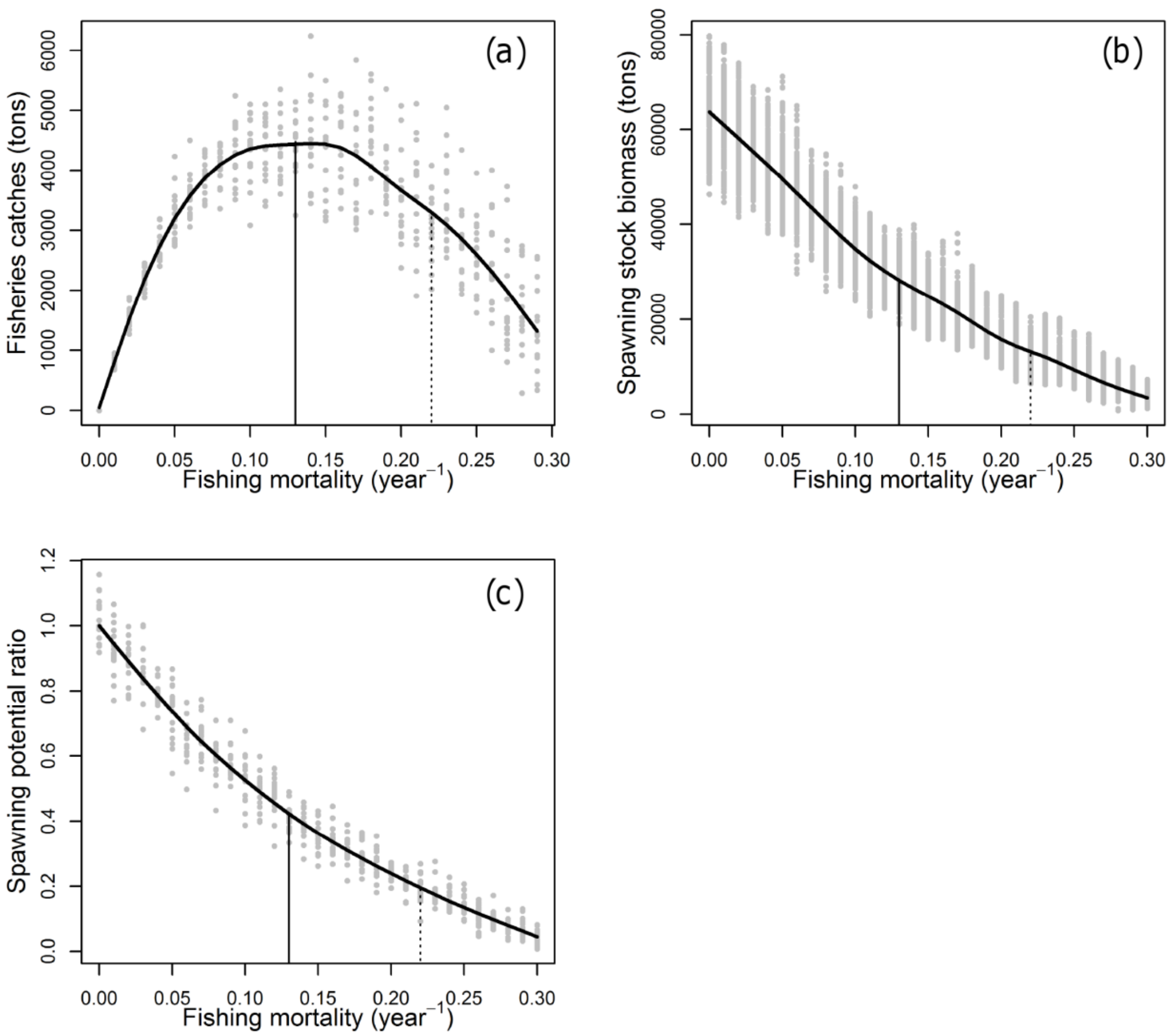

Fig. 7. Median trajectories of catch over initial catch for (a,e) red grouper (*Epinephelus morio*), (b,f) other large predators, (c,g) small predators, and (d,h) forage fish and invertebrates, (a,b,c,d) in the absence and (e,f,g,h) in the presence of episodic events of natural mortality (*M*), under three total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework. The three TAC scenarios assume that a TAC is implemented for red grouper every three years and that the σ_{OFL} parameter, which reflects scientific uncertainty, is equal to 0.36. The probability of overfishing considered acceptable (P*) differs between the three scenarios (0.3, 0.4, or 0.5). The median trajectories displayed in panels **(e,f,g,h)** were obtained under the scenario of episodic events of *M* shown in Fig. 5. One hundred simulation replicates were run to produce these plots.

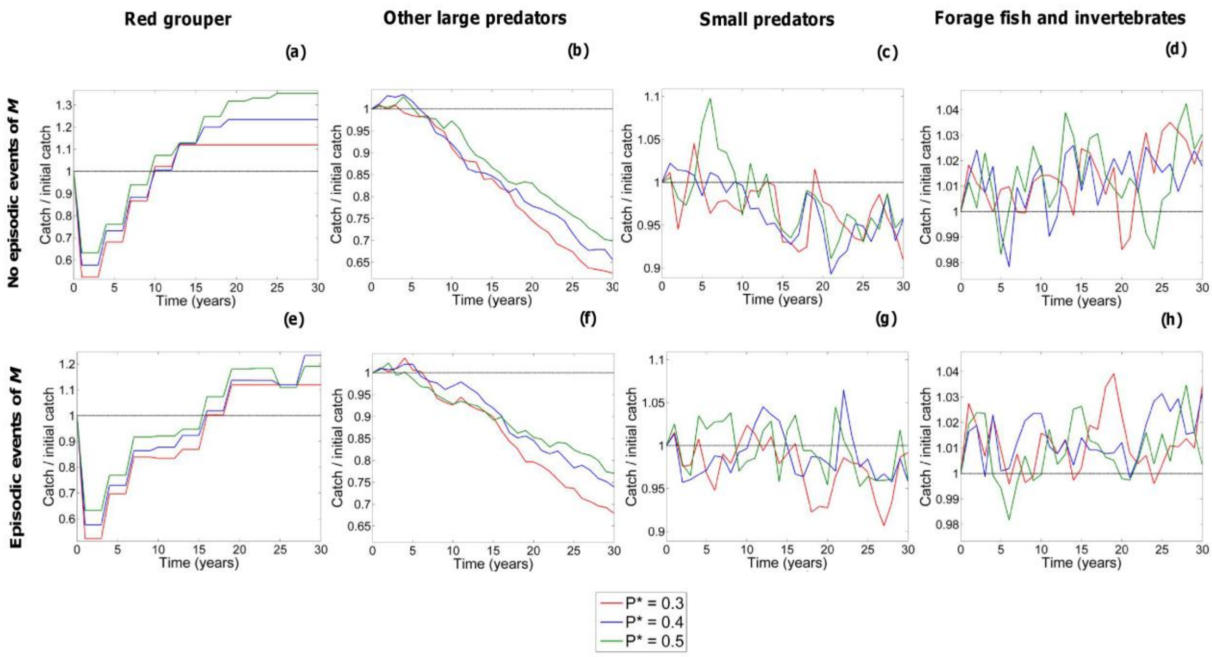

Fig. 8. Median trajectories of biomass over initial biomass for (a,e) red grouper (*Epinephelus morio*), (b,f) other large predators, (c,g) small predators, and (d,h) forage fish and invertebrates, (a,b,c,d) in the absence and (e,f,g,h) in the presence of episodic events of natural mortality (*M*), under three total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework. The three TAC scenarios assume that a TAC is implemented for red grouper every three years and that the σ_{OFL} parameter, which reflects scientific uncertainty, is equal to 0.36. The probability of overfishing considered acceptable (P*) differs between the three scenarios (0.3, 0.4, or 0.5). The median trajectories displayed in panels **(e,f,g,h)** were obtained under the scenario of episodic events of *M* shown in Fig. 5. One hundred simulation replicates were run to produce these plots.

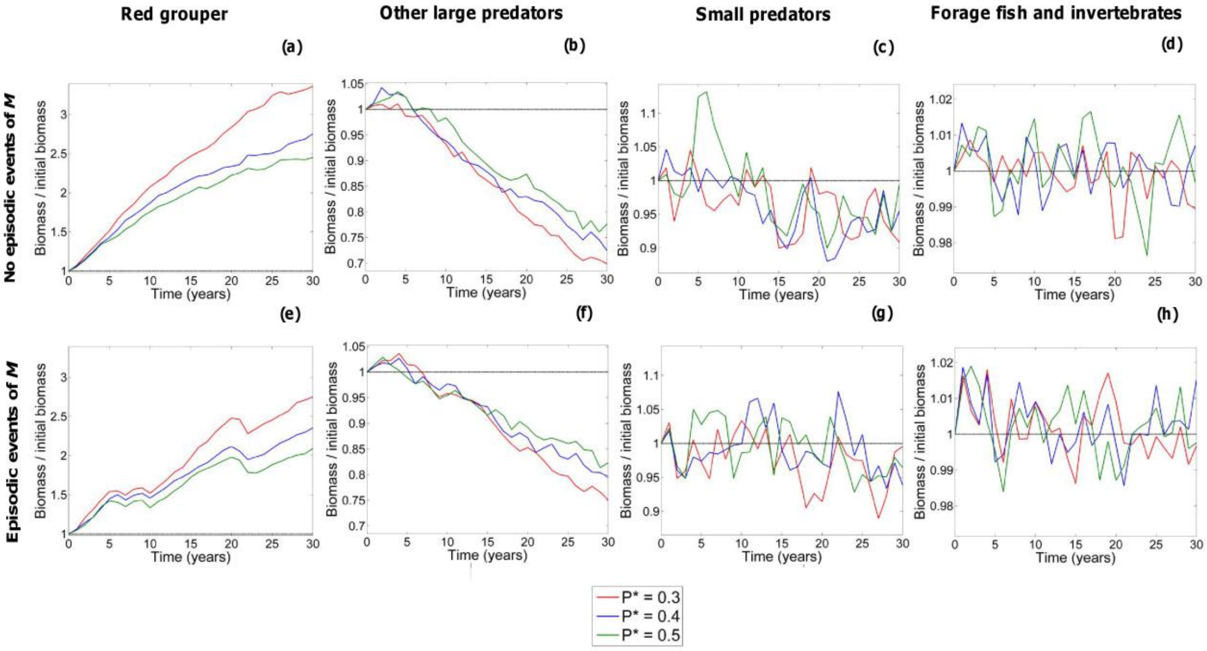

Fig. 9. Median trajectories of fishing mortality rate (*F*) over fishing mortality rate resulting in maximum sustainable yield (F_{msy}) for red grouper (*Epinephelus morio*), (a) in the absence and (b) in the presence of episodic events of natural mortality (*M*), under three total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework. The three TAC scenarios assume that a TAC is implemented for red grouper every three years and that the σ_{OFL} parameter, which reflects scientific uncertainty, is equal to 0.36. The probability of overfishing considered acceptable (P*) differs between the three scenarios (0.3, 0.4, or 0.5). The median trajectories displayed in panel **(b)** were obtained under the scenario of episodic events of *M* shown in Fig. 5. One hundred simulation replicates were run to produce these plots.

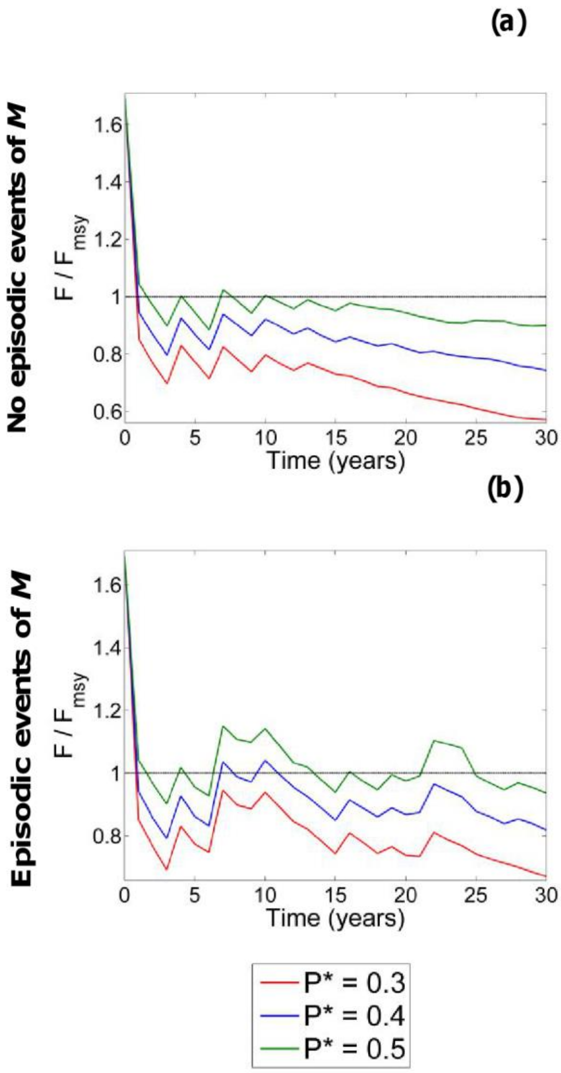

Fig. 10. Performance measures of three total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework, (a,b,c,d) in the absence and (e,f,g,h) in the presence of episodic events of natural mortality (*M*). The three TAC scenarios assume that a TAC is implemented for red grouper every three years and that the σ_{OFL} parameter, which reflects scientific uncertainty, is equal to 0.36. The probability of overfishing considered acceptable (P*) differs between the three scenarios (0.3, 0.4, or 0.5). The performance measures displayed in panels **(e,f,g,h)** were obtained under the scenario of episodic events of *M* shown in Fig. 5. One hundred simulation replicates were run to produce all box plots. Prob. avoid overfished = probability that red grouper is not being overfished - Prob. avoid collapse = probability that red grouper is not undergoing stock collapse – Net

present value = net present value of discounted revenues from red grouper catch – Stability of the catch = stability of red grouper catch.

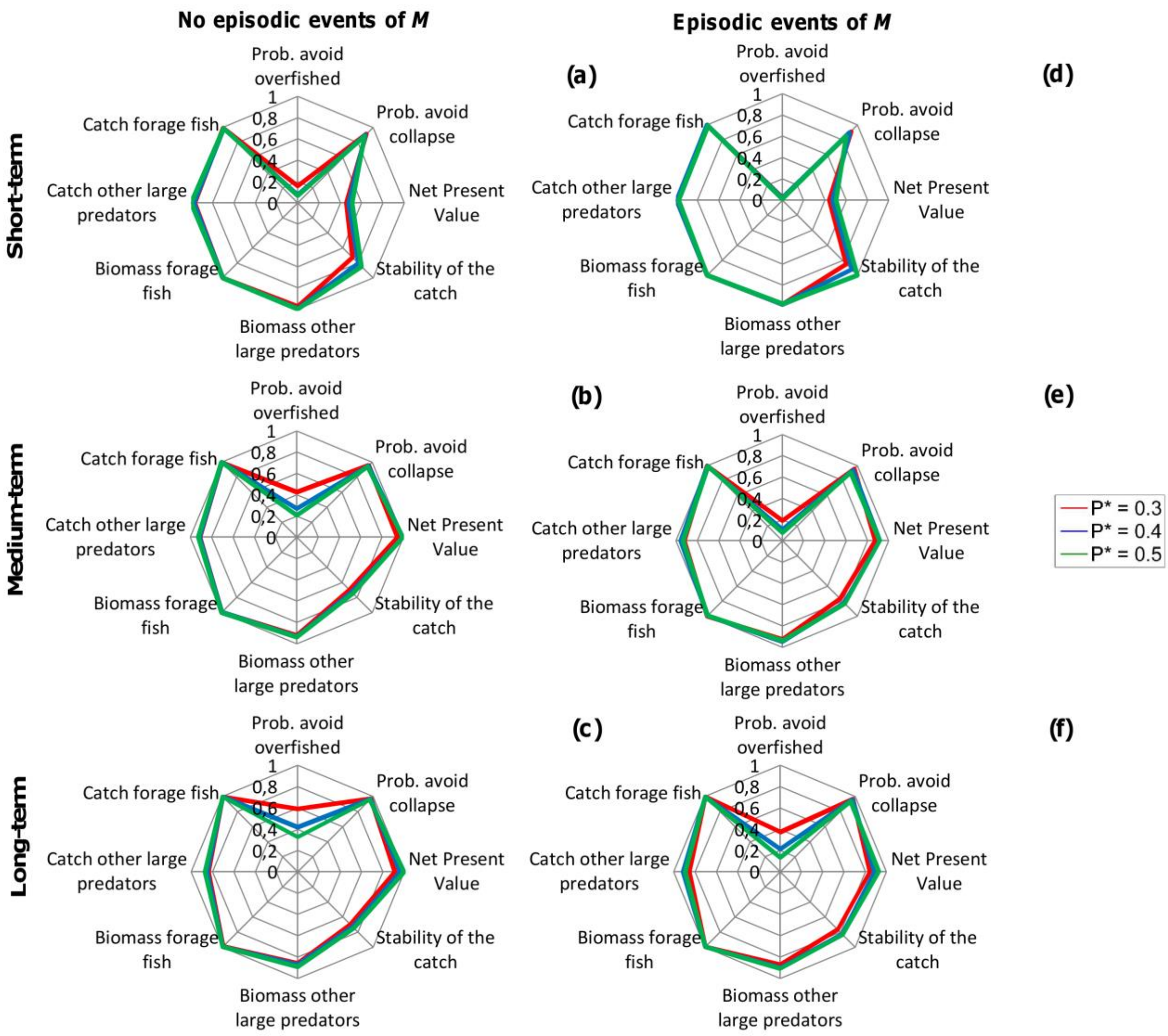

Fig. 11. Median performance of three total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework (normalized if necessary (*) so that 1 = good and 0 = poor performance), (a,b,c) in absence and (d,e,f) in the presence of episodic events of natural mortality (*M*). The three TAC scenarios assume that a TAC is implemented for red grouper every three years and that the σ_{OFL} parameter, which reflects scientific uncertainty, is equal to 0.36. The probability of overfishing considered acceptable (P*) differs between the three scenarios (0.3, 0.4, or 0.5). The performance measures displayed in panels **(d,e,f)** were obtained under the scenario of episodic events of *M* shown in

Fig. 5. One hundred simulation replicates were run to produce all radial graphs. Prob. avoid overfished = probability that red grouper is not being overfished - Prob. avoid collapse = probability that red grouper is not undergoing stock collapse – Net present value = net present value of discounted revenues from red grouper catch – Stability of the catch = stability of red grouper catch. (*) The probabilities that red grouper is not being overfished and that red grouper is not undergoing stock collapse naturally range between 0 and 1, so these two performance metrics were not normalized.

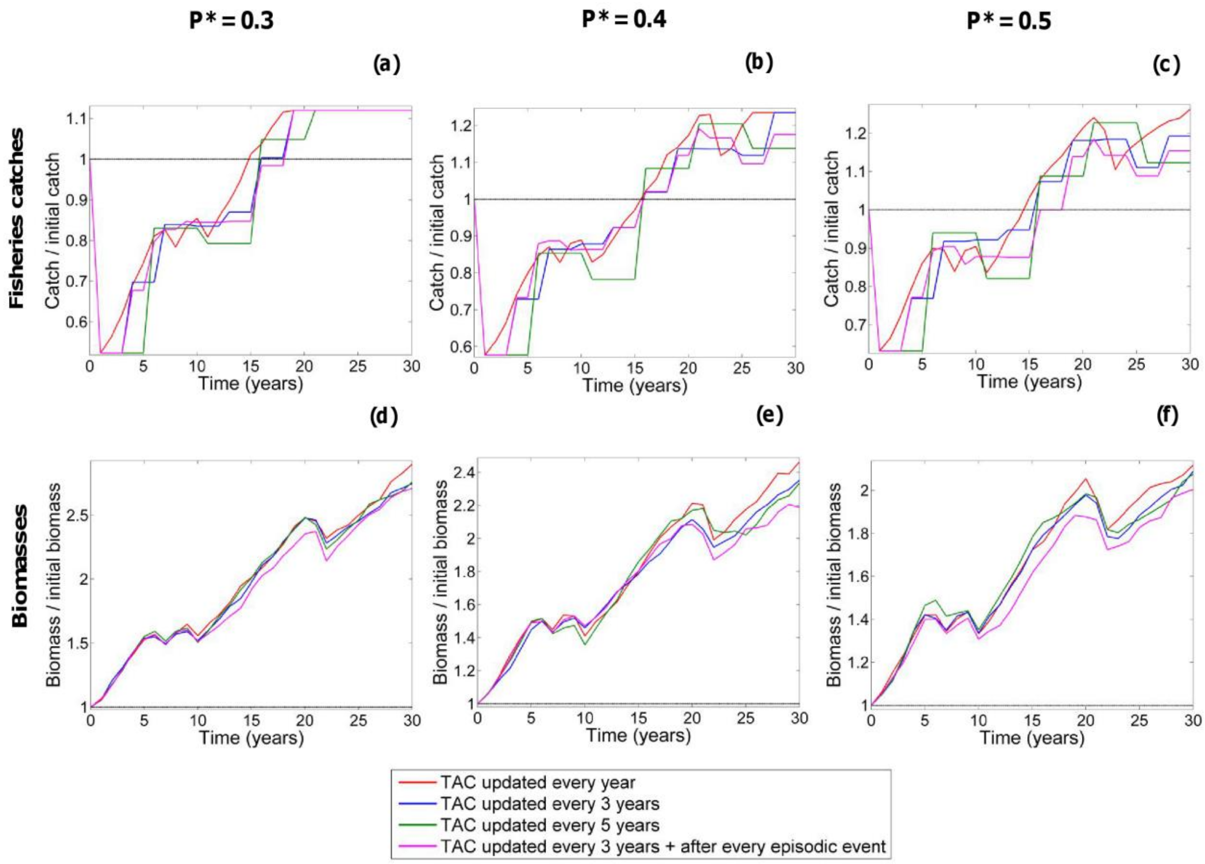

Fig. 12. Median trajectories of (a,b,c) catch over initial catch and (d,e,f) biomass over initial biomass for red grouper (*Epinephelus morio*), in the presence of episodic events of natural mortality (*M*), under several total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework. All TAC scenarios assume that the σ_{OFL} parameter, which reflects scientific uncertainty, is equal to 0.36, and that the TAC of red grouper is updated every year, every three years, every five years, or every three

years and every year following an episodic event of *M*. The probability of overfishing considered acceptable (P*) is set to 0.3 for **(a,d)**, 0.4 for **(b,e)** and 0.5 for **(c,f)**. All median trajectories were obtained under the scenario of episodic events of *M* shown in Fig. 5. One hundred simulation replicates were run to produce all plots.

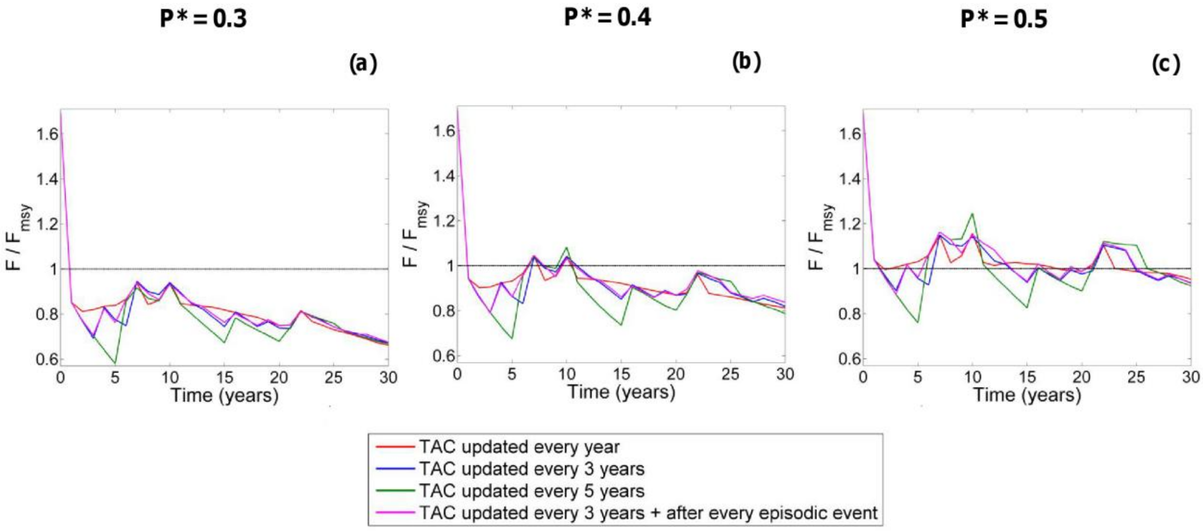

Fig. 13. Median trajectories of fishing mortality rate (*F*) over fishing mortality rate resulting in maximum sustainable yield (F_{msy}) for red grouper (*Epinephelus morio*), in the presence of episodic events of natural mortality (*M*), under several total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework. All TAC scenarios assume that the σ_{OFL} parameter, which reflects scientific uncertainty, is equal to 0.36, and that the TAC of red grouper is updated every year, every three years, every five years, or every three years and every year following an episodic event of *M*. The probability of overfishing considered acceptable (P*) is set to 0.3 for **(a)**, 0.4 for **(b)** and 0.5 for **(c)**. All median trajectories were obtained under the scenario of episodic events of *M* shown in Fig. 5. One hundred simulation replicates were run to produce all plots.

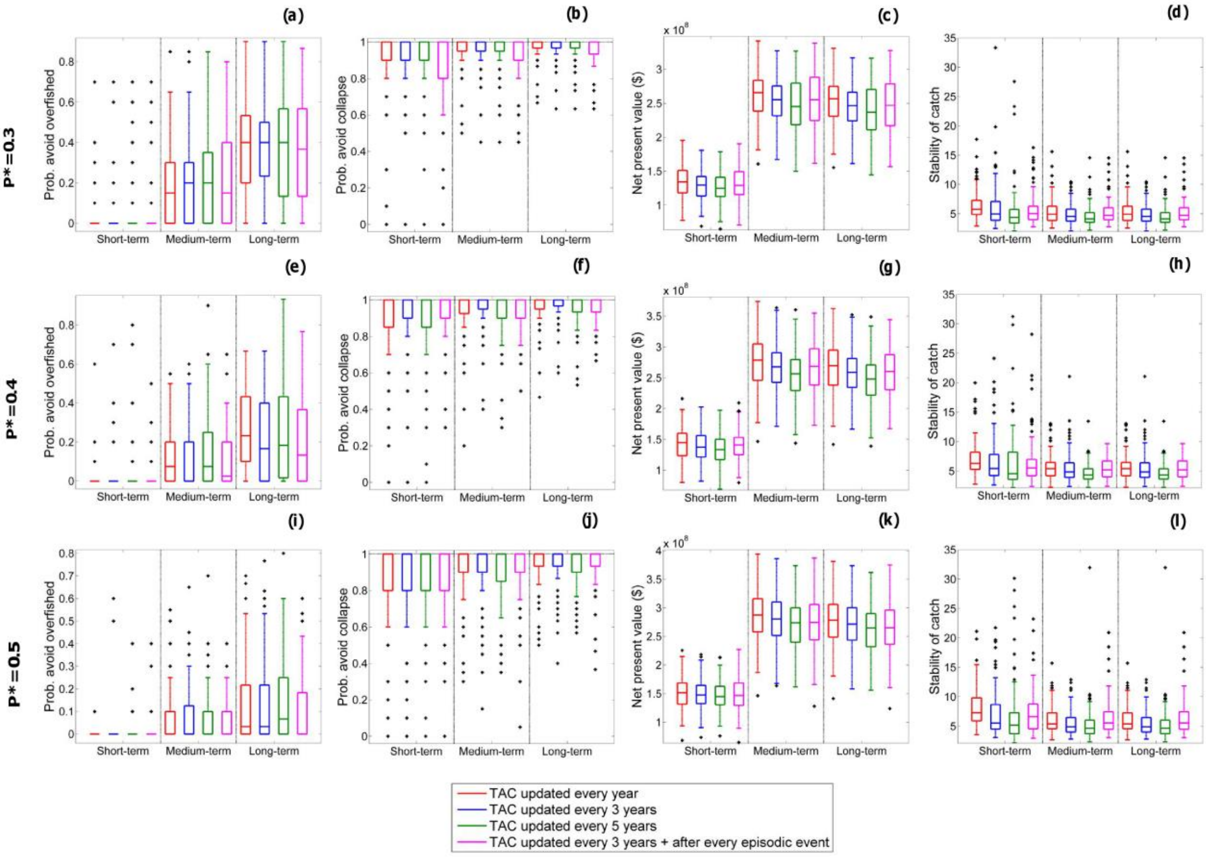

Fig. 14. Performance measures of total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework, in the presence of episodic events of natural mortality (*M*). TAC scenarios assume that the σ_{OFL} parameter, which reflects scientific uncertainty, is equal to 0.36, and that the TAC of red grouper is updated every year, every three years, every five years, or every three years and every year following an episodic event of *M*. The probability of overfishing considered acceptable (P*) is equal to 0.3 for **(a,b,c,d)**, 0.4 for **(e,f,g,h)** and 0.5 for **(i,j,k,l)**. One hundred simulation replicates were run to produce all box plots. Note that, for **(d,h,l)**, extreme outliers were removed for display purposes; these extreme outliers are displayed in Fig. H. Prob. avoid overfished = probability that red grouper is not being overfished - Prob. avoid collapse = probability that red grouper is not undergoing stock collapse – Net present value = net present value of discounted revenues from red grouper catch – Stability of the catch = stability of red grouper catch.

Tables

Table 1. High trophic level (HTL) groups explicitly considered in the OSMOSE-WFS model. Species of a given HTL group exhibit similar life history characteristics, body size ranges, diets and exploitation patterns. Some individual species constitute their own group, as they are emblematic to the West Florida Shelf and of high economic importance. A reference species was identified for each of the HTL groups (indicated in bold). Growth, reproduction, mortality and diet parameters of each group are those of the reference species of the group (given in Appendix D). The category of each HTL group ("large predator", "small predator", or "forage fish and invertebrates") is indicated.

HTL group	Category of HTL group	Species
King mackerel	Large predator	**King mackerel (*Scomberomorus cavalla*)**
Amberjacks	Large predator	**Greater amberjack (*Seriola dumerili*)** , banded rudderfish (*Seriola zonata*), lesser amberjack (*Seriola fasciata*)
Red grouper	Large predator	**Red grouper (*Epinephelus morio*)**
Gag grouper	Large predator	**Gag grouper (*Mycteroperca microlepis*)**
Red snapper	Large predator	**Red snapper (*Lutjanus campechanus*)**
Sardine-herring-scad complex	Forage fish and invertebrates	**Scaled sardine (*Harengula jaguana*)**, Spanish sardine (*Sardinella aurita*), Atlantic thread herring (*Opisthonema oglinum*), round scad (*Decapterus punctatus*), menhadens (*Brevoortia* sp.)
Anchovies and silversides	Forage fish and invertebrates	**Bay anchovy (*Anchoa mitchilli*)**, striped anchovy (*Anchoa hepsetus*), silversides (Atherinidae spp.), alewife (*Alosa* sp.)
Coastal omnivores	Forage fish and invertebrates	**Pinfish (*Lagodon rhomboides*)**, spottail pinfish (*Diplodus holbrooki*), orange filefish (*Aluterus schoepfii*), fringed filefish (*Monacanthus ciliatus*), planehead filefish (*Monacanthus hispidus*), orangespotted filefish (*Cantherhines pullus*), honeycomb filefish (*Acanthostracion polygonius*), Atlantic spadefish (*Chaetodipterus faber*), scrawled cowfish (*Lactophrys quadricornis*), pufferfish (Tetraodontidae spp.)
Reef carnivores	Small predators	**White grunt (*Haemulon plumieri*)**, black sea bass (*Centropristis striata*), rock sea bass (*Centropristis philadelphica*), belted sandfish (*Serranus subligarius*), longtail bass (*Hemanthias leptus*), butter hamlet (*Hypoplectus unicolor*), creole fish (*Paranthias furcifer*), splippery dick (*Halichoeres bivittatus*), painted wrasse (*Halichoeres caudalis*), yellowhead wrasse (*Halichoeres garnoti*), bluehead (*Thalassoma bifasciatum*), reef croaker (*Odontoscion dentex*), jackknife-fish (*Equetus lanceatus*), leopard toadfish (*Opsanus pardus*), scopian fish (Scorpaenidae spp.), bigeyes (Priacanthidae spp.), littlehead porgy (*Calamus proridens*), jolthead porgy (*Calamus bajonado*), saucereye progy (*Calamus calamus*), whitebone progy (*Calamus leucosteus*), knobbed progy (*Calamus nodosus*), French grunt (*Haemulon flavolineatum*), Spanish grunt (*Haemulon macrostomum*), margate (*Haemulon album*), bluestriped grunt (*Haemulon sciurus*), striped grunt (*Haemulon striatum*), sailor's grunt (*Haemulon parra*), porkfish (*Anisotremus virginicus*), neon goby (*Gobiosoma oceanops*)
Reef omnivores	Forage fish and invertebrates	**Doctorfish (*Acanthurus chirurgus*)**, other surgeons (Acanthuridae spp.), blue angelfish (*Holacanthus bermudensis*), gray angelfish (*Pomacanthus arcuatus*), cherubfish (*Cantropyge argi*), rock beauty (*Holacanthus tricolor*), cocoa damselfish (*Pomacentrus variabilis*), bicolor damselfish (*Pomacentrus partitus*), beau gregory (*Pomacentrus leocostictus*), yellowtail damselfish (*Microspathodon chrysurus*), seaweed blenny (*Parablennius marmoreus*), striped parrotfish (*Scarus croicensis*), bidled goby (*Coryphopterus glaucofraenum*), Bermuda chub (*Kyphossus sectarix*)
Shrimps	Forage fish and	**Pink shrimp (*Farfantepenaeus duorarum*)**, brown

	invertebrates	shrimp (*Farfantepenaeus aztecus*), white shrimp (*Litopenaeus setiferus*), other shrimp species
Large crabs	Small predators	**Blue crab (*Callinectes sapidus*)**, stone crabs (*Menippe mercenaria* and *Menippe adina*), horseshoe crab (*Limulus polyphemus*), hermits crab (e.g., *Pylopagurus operculatus* and *Clibanaris vittatus*), spider crabs (e.g., *Stenocionops furcatus*), arrow crabs (e.g., *Stenorynchus seticornis*)

Table 2. Composite performance indices for different total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework, under a short-term perspective (considering the first 10 years of simulations), a medium-term perspective (considering the first 20 years of simulations), and a long-term perspective (considering the 30 years of simulations).

Question addressed	Value of P*	Index under a short-term perspective	Index under a medium-term perspective	Index under a long-term perspective
How does the value of the buffer influence fisheries management performance for red grouper?	0.3	6.18	6.84	6.86
	0.4	6.21	6.78	6.80
	0.5	6.29	6.75	6.79
How do TAC strategies for red grouper perform in the presence of episodic events of natural mortality? – Case where episodic events of natural mortality occur	0.3	6.20	6.63	6.67
	0.4	6.28	6.67	6.68
	0.5	6.30	6.59	6.62

Table 3. Composite performance indices for different total allowable catch (TAC) scenarios tested with the OSMOSE management strategy evaluation framework, under a short-term perspective (considering the first 10 years of simulations), a medium-term perspective (considering the first 20 years of simulations), and a long-term perspective (considering the 30 years of simulations). The question being addressed here is: "Is there a benefit to updating the TAC of red grouper more frequently in a context of episodic events of natural mortality?"

Value of P*	Frequency of TAC updates	Index under a short-term perspective	Index under a medium-term perspective	Index under a long-term perspective
0.3	Every year	6.12	6.61	6.68
	Every 3 years	6.01	6.47	6.51
	Every 5 years	5.88	6.42	6.47
	Every 3 years + after every episodic event of natural mortality	5.97	6.52	6.55
0.4	Every year	6.26	6.65	6.70
	Every 3 years	6.08	6.50	6.51
	Every 5 years	5.89	6.35	6.37
	Every 3 years + after every episodic event of natural mortality	6.06	6.52	6.52
0.5	Every year	6.33	6.60	6.60
	Every 3 years	6.09	6.46	6.45
	Every 5 years	5.96	6.40	6.37
	Every 3 years + after every episodic event of natural mortality	6.16	6.53	6.52