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Predicting shifting sustainability trade-offs in marine finfish aquaculture under climate change

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Abstract

Defining sustainability goals is a crucial but difficult task because it often involves the quantification of multiple interrelated and sometimes conflicting components. This complexity may be exacerbated by climate change, which will increase environmental vulnerability in aquaculture and potentially compromise the ability to meet the needs of a growing human population. Here, we developed an approach to inform sustainable aquaculture by quantifying spatio-temporal shifts in critical trade-offs between environmental costs and benefits using the time to reach the commercial size as a possible proxy of economic implications of aquaculture under climate change. Our results indicate that optimizing aquaculture practices by minimizing impact (this study considers as impact a benthic carbon deposition ≥ 1 g C m^{-2} day^{-1}) will become increasingly difficult under climate change. Moreover, an increasing temperature will produce a poleward shift in sustainability trade-offs. These findings suggest that future sustainable management strategies and plans will need to account for the effects of climate change across scales. Overall, our results highlight the importance of integrating environmental factors in order to sustainably manage critical natural resources under shifting climatic conditions.

KEYWORDS

aquaculture, mechanistic predictive models, Mediterranean Sea, regional climate models, seabass, trade-offs

1 | INTRODUCTION

Sustainability is a complex, layered, and inherently multidisciplinary concept that spans multiple fields including environmental science, social policy, and economics, also known as the three dimensions of sustainable development (ICSU & ISSC, 2015). The environment and the services it provides represent the base layer upon which social and economic policy relies. Sustainable development, which strives to meet the needs of a growing human population while safeguarding Earth's stressed life-support systems (ICSU & ISSC, 2015), is becoming increasingly important in an era of global change and large-scale biodiversity decline (Barnosky et al., 2011, 2012; Cardinale et al., 2012). Most national and international legislative efforts have highlighted the critical role that sustainability plays in ensuring the welfare of current and future generations.

The 2030 Agenda for Sustainable Development (ICSU & ISSC, 2015), the Sustainable Development Goals (SDGs and related targets, adopted in 2015), the Mediterranean Strategy for Sustainable Development 2016–2025 (UNEP/MAP, 2016), and the Paris Agreement of the Conference of the Parties (COP21) of the United Nations Framework Convention on Climate Change have greatly influenced and addressed the exploitation of natural resources at sea (i.e., such as fishery and aquaculture) (Visbeck, 2018). Although the importance of environmental sustainability has been widely recognized and supported by integrated frameworks (Costanza et al., 1997), very few attempts have been made to objectively quantify and operationally define the existing trade-offs between the three sustainability components in the aquaculture sector (Tlusty & Thorsen, 2017). Operationally defining sustainability goals under current conditions is difficult as it involves the quantification of multiple, interrelated and often-conflicting components. The complexity of this task is expected to be exacerbated by climate change and, in particular, rising temperatures which will increase environmental vulnerability and, in applied fields such as aquaculture, will have important social and economic repercussions that are likely to extend beyond national borders. Hence, local managers and policy-makers need comprehensive credible, salient, and legitimate baseline knowledge in order to quantify the environmental trade-offs to be integrated into social and economic scenarios for a sustainable development in space and time. Such information would allow the implementation of optimal ecosystem-based management strategies and strengthen the science-policy nexus (i.e., the relationship between environment-related science and policy FAO, 2016; Hickey, Forest, Sandall, Lalor, Keenan, 2013).

Aquaculture has historically focused on maximizing productivity and economic returns on very short timescales. Although such practices can yield positive outcomes in the short term, the net results in the medium to long term are often negative from a social, environmental and economic perspective. Overall, future aquaculture development needs to adopt a more integrated approach that balances social, economic and environmental objectives to ensure a sustainable harvest of natural resources over multiple time horizons (ICSU & ISSC, 2015). Here, we developed an approach to quantify spatio-temporal shifts of critical trade-offs between environmental costs and benefits using the time to reach the commercial size as a possible proxy of commercial implications of aquaculture under climate change. To forestall shifts will allow one to inform policy changes and avoid the risk for a growing disparity of responses between Mediterranean countries and societies (UNEP/MAP, 2016).

The described approach relies on predictive models based on fundamental biological characteristics of species (i.e., Functional Traits [FT], sensu Schoener, 1986; Sarà, Rinaldi, & Montalto, 2014). At scales relevant to national management (Economic Exclusive Zones, EEZ, Supporting information Figures S1 and S2), the development of FT-based approaches (Schoener, 1986) can be used to generate the kinds of species- and site-specific mechanistic predictions of environmental costs and benefits needed to quantify trade-offs and inform sustainable development objectives (Sarà, Mangano, Johnson, & Mazzola, 2018). Such a mechanistic approach is critical for devising an optimal spatial allocation strategy that simultaneously maximizes commercial benefits (production) and minimizes environmental effects (pollution). Indeed, by quantifying how the relationship between biomass productivity and environmental impact (i.e., the amount of organic loading derived from aquaculture; LOAD) of changes over space and time, our approach can be used to design future management plans that are optimal across multiple scales. On this basis, stakeholders could identify and implement proactive, site-specific management strategies tailored to target species. Once such relationship is spatially-contextualized and mapped, it represents, in practice, the quantitative informational baseline that scientists, policy-makers, and stakeholders need to produce management strategies and plans that will also adapt to the combined multiple pressures of climate change (Kearney & Porter, 2009; Pacifici et al., 2015; Payne et al., 2015; Sarà, Porporato, Mangano, Mieszkowska, 2018; Shelton, 2014).

Overall, the proposed approach will document spatio-temporal patterns of covariation between environmental cost and benefit maximized changes under current and future climate conditions and narrowing the science-policy communication gap (Hickey et al., 2013). We chose the aquaculture sector as a model system to test how climate change (IPCC AR5 scenarios; 2015 vs. 2030 vs. 2050) will affect the sustainable management of a critical natural resource. Mechanistic FT-based models are ideal in aquaculture and in most intensive terrestrial cultures (Koenigstein, Mark, Gößling-Reisemann, Reuter, & Poertner, 2016) since the effects of species interactions (e.g., competition for space and resource and predator-prey relationships) can be controlled *via* active management. We applied such mechanistic FT-based models on the Mediterranean seabass, *Dicentrarchus labrax* (Supporting information Figure S3). The Mediterranean seabass is an ideal model as it is one of the most traded species in the world and one of the fastest-growing cultivated fish in the Mediterranean Sea (FAO, 2016). Additionally, the Mediterranean seabass may represent the candidate target for Northern Europe aquaculture, owing to expected climate-induced temperature increases in the region in future; the species has an affinity toward the future expected temperature in this area (EUMOFA, 2016).

2 | MATERIALS AND METHODS

A framework (Figure 1) comprising of six steps was built, exploiting the power of the mechanistic-based models Dynamic Energy Budget (the DEB; Kooijman, 2010) and FiCIM (Brigolin et al., 2014) as described here below.

2.1 | STEP 1—The dynamic energy budget (DEB) model

The DEB model (Supporting information Figure S3) involves a complete theoretical assessment at the whole-organismal level, to link habitat features, functional traits, and life history of any living organism (Kooijman, 2010). DEB was selected for this study as a suitable model to provide a whole-organismal approach, as DEB enables one to elucidate how biologically and ecologically relevant responses depend on environmental conditions (Kearney, Simpson, Raubenheimer, & Helmuth, 2010; Sarà et al., 2012). Central to the DEB theory is the concept that food and body temperature (BT) are the primary drivers of an individual's metabolic machinery (Sarà, Palmeri, Montalto, Rinaldi, & Widdows, 2013). The amount of ingested energy available for biological processes is regulated within the DEB

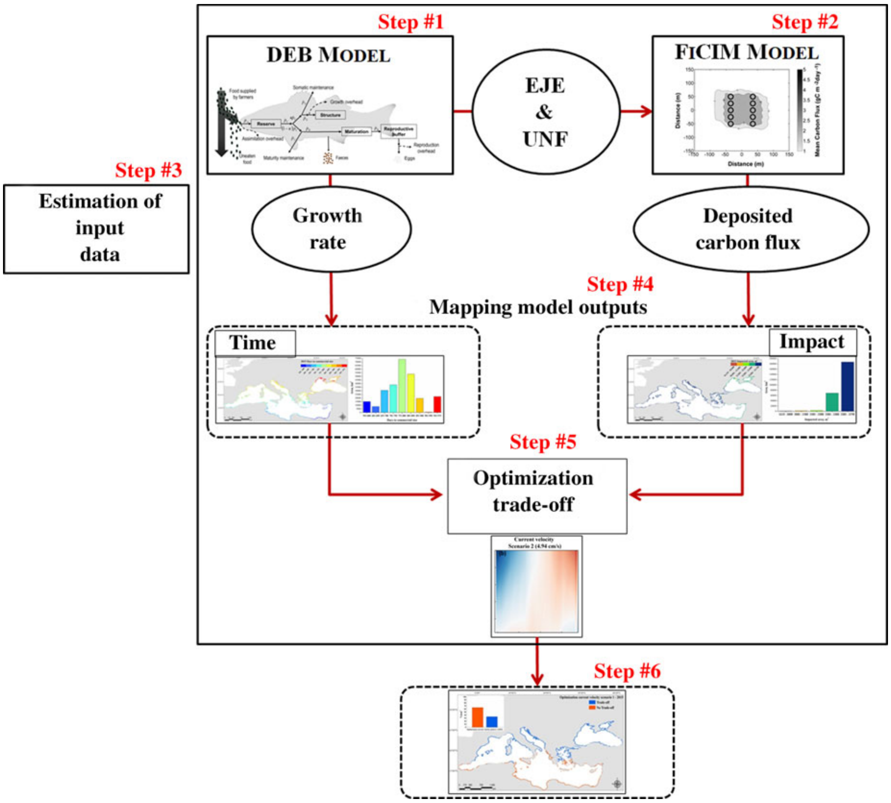

FIGURE 1 Six-step framework based on mechanistic models (DEB and FiCIM) used to obtain mechanistic-based spatial explicit optimization [Colour figure can be viewed at wileyonlinelibrary.com]

theory by the Holling's functional responses (Holling, 1959). Once food is ingested, the amount of energy that flows through the organism depends at some extent on physiological rates. As all physiological rates depend on body temperature, BT is an important driver, in particular for ectotherms, such as fish and shellfish, as their BT is close to that of their surroundings. The effect of temperature on metabolism follows the Arrhenius relationship (Kooijman, 2010), which allows one to quantify how metabolic rates change within the range of tolerance in each species; such range implicitly sets the limits of the fundamental thermal niche of a given species (Kearney & Porter, 2009).

To provide reliable predictions, the *Dicentrarchus labrax* model was implemented through a systematic review (Mangano, Sarà, & Corsolini, 2017) performed to deliver some preliminary parameters needed to further calibrate the *Dicentrarchus labrax* DEB model. Details about the model calibration and validation are given in the Supporting information section Tables S1, S2, and S3; Figure S4. The Arrhenius formulation includes a specie-specific parameter, i.e., the Arrhenius temperature (TA), which, in this study, was estimated as the slope of the linear regression between the logarithm of fish oxygen consumption rate and absolute temperature. The lower and upper boundaries of the BT tolerance range were extrapolated from the literature (Claireaux & Lagardère, 1999; Claireaux & Lefrançois, 2007; Dalla Via, Tappeiner, & Bitterlich, 1987; Person-Le Ruyet, Mahé, Le Bayon, & Le Delliou, 2004); these parameters are listed in Supporting information Table S1. Once the DEB model was validated, the outputs were used to map the productivity index TIME (see Figure 1) and feed the FiCIM model, as described below. Details about the model calibration and validation are provided in the Supporting information Model validation section and Figure S4.

2.2 | STEP 2—FiCIM (Fish cage Integrated Model; Brigolin et al., 2014)

Organic matter accumulation and associated negative effects on benthic communities has been identified as a key negative interaction of fish cages with the surrounding marine environment (Hargrave, 2005). Here, we simulated this impact by coupling the DEB model described in STEP 1 with the particle tracking and deposition modules of the FiCIM (Brigolin et al., 2014). These modules allow one to obtain 2D maps of elemental fluxes of organic Carbon [g C m^{-2} day^{-1}] at the water–sediment interface on the basis of the amount and composition of organic matter particles released by a fish farm as feces and uneaten feed (Supporting information Figure S5). The model requires the following as input: (a) time series of the amount and elemental composition of uneaten feed and feces released by fish farms; (b) time series of water currents (see STEP 3); (c) bathymetry of the area in which a fish farm is located.

Fish cage Integrated Model produces output time series of fluxes of organic C, N, and P deposited on the seabed surrounding a fish farm. To provide a synthetic index, the average deposition of organic C was computed, named LOAD hereafter, expressed as g C m^{-2} day^{-1}, for each grow-out production phase, at each grid point. Subsequently, based on Cromey, Black, Edwards, and Jack (1998) and Hargrave, Holmer, and Newcombe (2008), an impact threshold, i.e., 1 g C m^{-2} day^{-1} was set, above which a grid point is classified as impacted (i.e., areas in which LOAD exceeds the threshold).

The species-specific LOAD index takes into account the effects of prolonged organic matter accumulation underneath a fish farm, which depletes the concentration of dissolved oxygen in surface sediment, leading to changes in macrofauna community structure (Cromey, Nickell, & Black, 2002; Hargrave et al., 2008). LOAD was determined on a grid of 5 × 5 m resolution by tracking 10,000 particles *per* day. The parameters used in the deposition module and their references are reported in Supporting information Table S4. The initial positions of fecal particles and uneaten feed pellets were randomly chosen within, respectively, the volume at a fish cage and its surface. The settling velocity of each particle was randomly selected from a Gaussian distribution (parameters are reported in Supporting information Table S4). The model was coded in Fortran and run on SCSCF (www.dais.unive.it/scscf), a multiprocessor cluster system owned by Ca' Foscari University of Venice.

2.3 | STEP 3—Estimation of input data

In principle, all forcings needed to run the DEB seabass model and FiCIM should be estimated for the whole study area on the basis of site-specific data; however, in practice, this is not feasible, both because of the lack of a comprehensive dataset and the computational effort required by the FiCIM model. Therefore, to be consistent with the aim of the paper, we proceeded with the following: (a) discretization of the study area, (b) estimation of DEB forcing function, and (c) estimation of FiCIM forcing function.

2.3.1 | Discretization of the study area

In order to identify the study area, a 10 km coastline buffer with bathymetric data and excluded areas deeper than 200 meters was clipped, which would lie outside the continental shelf. The resulting study area extended along a buffer of 10 km across the continental shelf of the Mediterranean and Black Sea (Supporting information Figure S6); the total surface was approximately 262,395 km^2. Bathymetric data were accessed from the General Bathymetric Chart of the Ocean (GEBCO_2014, http://www.gebco.net/) at 30 s arc resolution (~1 km).

2.3.2 | Estimation of the DEB forcing functions

As stated, DEB models require body temperature (BT) as input time series. To apply the approach visualized in Figure 1 to the whole study area, we took the Sea Surface Temperature (SST) as a proxy of BT. Time series of SST data were estimated from the results of the EURO-CORDEX initiative (Jacob et al., 2014; Coordinated Regional Climate Downscaling Experiment). This Regional Climate Model is based on the IPCC Fifth Assessment Report (AR5) CMIP5 (Coupled Model Intercomparison Project). Data were downloaded (https://esgf-index1.ceda.ac.uk/projects/esgf-ceda/) concerning the Representative Concentration Pathways, RCP 4.5, with a spatial resolution of 0.11° (~12.5 km). Next, three time series of daily SST for the following years: 2012–2014, 2030–2032, and 2048–2050 were extracted, hereafter labeled 2015, 2030, and 2050, respectively, and rescaled the data at 1 km, the same spatial resolution of the bathymetry dataset (applying the nearest neighbor interpolation) (Kotlarski et al., 2014).

The study area was partitioned into subregions characterized by similar annual mean temperature for the three temperature scenarios. In order to obtain these subregions, we divided the range of average temperatures for each scenario into 0.5°C intervals and aggregated each grid point of the spatial domain within the resulting classes; each class then included all cells falling within "Similar Average Temperature Regions" (SATRs). Subsequently, we estimated an average 3-year SST time series for each SATR to be used as input to the DEB model. SST data in NetCDF format were transformed in comma-separated values (CSV) format suitable for the DEB model using software developed by NASA Goddard Institute for Space Studies (Panoply; GISS, http://www.giss.nasa.gov/tools/panoply/). All NetCDF files were handled using Climatic Data Operators (CDO) software (1.6.4 version; Max-Planck Institut für Meterologie). Daily SST values of each SATR were used to feed the DEB model as a proxy of individual BT to compute the spatial distributions of the outputs of the DEB model (TIME, the feces released every hour by an individual—EJE and the hourly amount of uneaten feed per individual—UNF).

2.3.3 | Estimation of FiCIM forcing functions

Dynamic Energy Budget and FiCIM were run in sequence for every SATR for each temperature scenario as follows: the first model produced the TIME index and the time series of EJE and UNF, which were used in turn as input for the FiCIM model to estimate the LOAD index.

Time series of the amount and elemental composition of uneaten feed (UNF) and feces (EJE) released by a fish farm were used to estimate daily emissions of a representative fish farm with 10 m high cylindrical cages with a diameter of 15 m, assuming a stocking density of 30 individual m^3, which leads to a biomass density at harvest of approximately 15 kg/m^3 (Halwart, Soto, & Arthur, 2007; Trujillo, Piroddi, & Jacquet, 2012). Details on the coupling among individuals, the ensemble of individuals stock in cages, and deposition modules in FiCIM are reported in Brigolin et al. (2014). The particle tracking module is computationally time-consuming and, therefore, it was not possible to run as many simulations as are the cells in which the study area was divided. Therefore, in order to find representative values of the hydrodynamic circulation and bathymetry necessary for the FiCIM models, we performed the following: (a) determined the location of fish cages within the study area, (b) estimated the distributions of the bathymetric and current data, and (c) computed the

25th, 75th, and 95th percentiles as representatives values of the two distributions. Fish cage positions (Supporting information Figure S1) were determined by means of an extensive survey carried out through Google Earth (last update June 2016) within the study area following the method described by Trujillo et al. (2012).

Depths at cage sites were extracted from the GEBCO dataset and the EMODnet bathymetry portal (http://www.emodnet-hydrography.eu/). Daily mean current velocity data were downloaded from the European MyOcean project for every cage in the Mediterranean Sea (Copernicus Marine Service - Ocean monitoring and forecasting service; http://www.myocean.eu/) produced by means of the NEMO Ocean model version 3.4 (Madec, 2008) on a regular grid with a spatial resolution of 1/16° (*ca.* 6–7 km) from the year 2014. Eastward and northward current velocity (m/s) data were downloaded and extracted the subset of data concerning the grid cells where the fish cages were kept. Synthetic current time series were generated, assuming that the current module and main axis were normally distributed around their 25th, 75th, and 95th percentiles. Variances were set on the basis of NEMO data analysis.

The sensitivity of the environmental impact indicator, LOAD, with respect to oceanographic conditions, was explored for the three percentiles considered (25th, 75th, and 95th) by combining the three representative depths (11.8 m, hereafter coded as −12; 19.0 and 43.6 m, hereafter coded as −44 m) with the three representative current velocities (1.18, 4.94 and 12.47 cm/s), thus obtaining nine oceanographic scenarios (see Supporting information Table S5).

2.4 | STEP 4—Mapping of model outputs

We ran the modeling system for each SATR using the forcing time series estimated as described previously for the three temperature scenarios (2015, 2030, and 2050) as input. Each simulation was run until an individual reached the standard commercial size of 500 g according to FAO statistics (http://www.fao.org/fishery/culturedspecies/Dicentrarchus_labrax/en). Finally, the two indices (TIME and LOAD) for each time period were mapped (Supporting information Figure S7).

2.5 | STEP 5—Optimization trade-off

2.5.1 | Modeling the trade-off

We used 1–3 degree polynomial regressions to quantify the trade-off between the environmental costs (area in m^2: LOAD) and benefits (time to reach commercial size, days: TIME) impact of aquaculture for each oceanographic scenario (current speeds of 1.18, 4.94, and 12.47 cm/s) and year (2015, 2030, and 2050). We then used information theory (corrected Akaike's information criterion, AICC) to select the model with the optimal polynomial degree. In all cases, the second-degree polynomial model was selected to describe the relationship between environmental and commercial impacts of aquaculture as an inverted parabola. The ascending section of the parabola represented a positive correlation between environmental and commercial components (no trade-off), whereas the descending section represented a negative correlation between environmental and commercial components (trade-off). Values found in the ascending section were color-coded in red (no trade-off), whereas those found in the descending section were color-coded in blue (trade-off) (Supporting information Figure S8).

2.5.2 | Commercial-to-environmental impact sensitivity analysis

An extensive sensitivity analysis was conducted to determine how the trade-off changed under different assumptions regarding the relative valuation of commercial and environmental components for each oceanographic scenario and year. To do so, we computed the z-scores of the commercial (z_C) and environmental (z_E) components by subtracting the mean from each value and dividing by the standard deviation. These dimensionless z-scores thus measure the "distance" between each component value and its mean in terms of the number of standard deviations; hence, z-scores that are negative lie below the mean and *vice versa*. We then computed the total impact as $z_{total} = z_C + a\ z_E$, where "*a*" represents a scalar used to alter the relative weight of commercial and environmental components on total impact. We further explored values ranging from 0 to 5 to determine the robustness of our results to different weightings of commercial and environmental components.

2.6 | STEP 6—Optimization spatial mapping

Optimization maps were produced joining the results obtained from the analysis carried out in STEP 5 with each SATR, both no trade-off and trade-off SATRs were represented. No trade-off indicates the regions where a reduction in TIME should also reduce the environmental LOAD and *vice versa*, while at the trade-off regions a reduction in TIME should increase the environmental LOAD and *vice versa*. Supporting information Figure S9 shows the difference in impacted areas between the 2015 and 2050 scenarios and between the 2030 and the 2050 scenarios.

3 | RESULTS

Our findings show that increasing temperatures under climate change will positively affect the time to reach commercial size (TIME, in days) according to a latitudinal gradient (Figure 2).

In particular, most areas will have an increase in TIME between 2015 (days = 939) versus 2030 (days = 956), whereas between 2015 and 2050 (days = 937), the length of coastline where the TIME will be shorter, will increase. The environmental impact of aquaculture (LOAD) was quantified by measuring the amount of total coastline area (m^2) affected by produced ejections (EJE) and uneaten feed (UNF) under multiple oceanographic conditions (intermediate oceanographic conditions shown in Figure 3; other conditions shown in Supporting information Table S5). The areas with

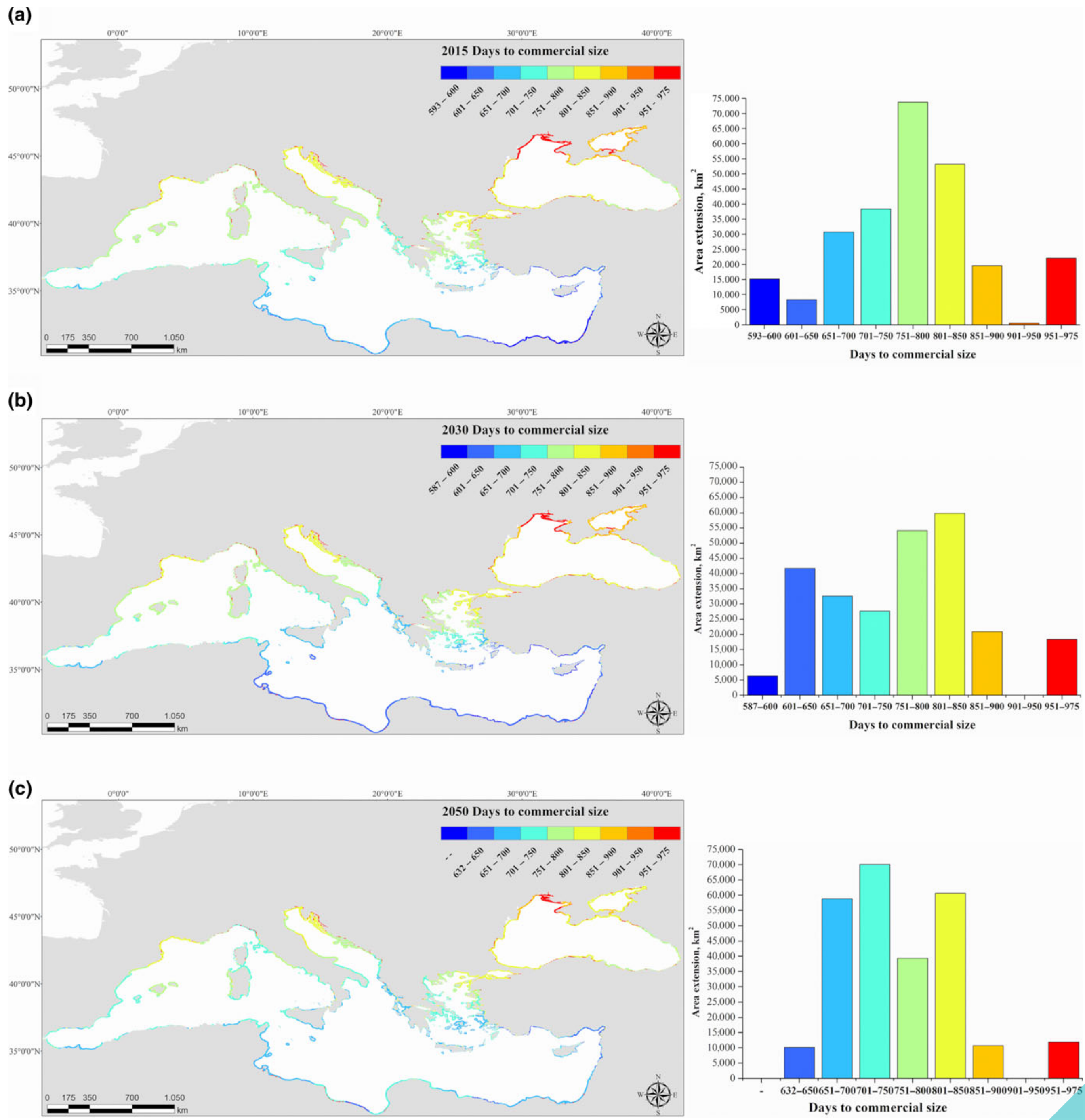

FIGURE 2 The time in days required to reach commercial size, from top to the bottom, respectively, across 2015, 2030, and 2050. Nine-day classes are reported (differences in the first class are to highlight, respectively: 2015 = 587–600; 2030 = 593–600; 2050 = –; other classes include 601–650, 651–700, 701–750, 751–800, 801–850, 851–900, 901–950, 951–975). Each histogram on the right side of the panel shows the number of km^2 within each class for each examined period [Colour figure can be viewed at wileyonlinelibrary.com]

increasing LOAD will increase between 2015 and future scenarios (Figure 3) with a heterogeneous spatial pattern (Supporting information Figure S7).

In general, these maps show that the spatial distributions of commercial and environmental changes will vary in complex ways over time. To determine the relationship between commercial and environmental changes as well as their covariation in space and time, we regressed the environmental against the commercial components using second-degree polynomials for each oceanographic scenario and year. Our analyses among the three oceanographic scenarios showed a unimodal relationship between environmental and commercial components (inverted parabola), with environmental and commercial components positively correlated in the ascending region and negatively correlated in the descending region (Figure 4).

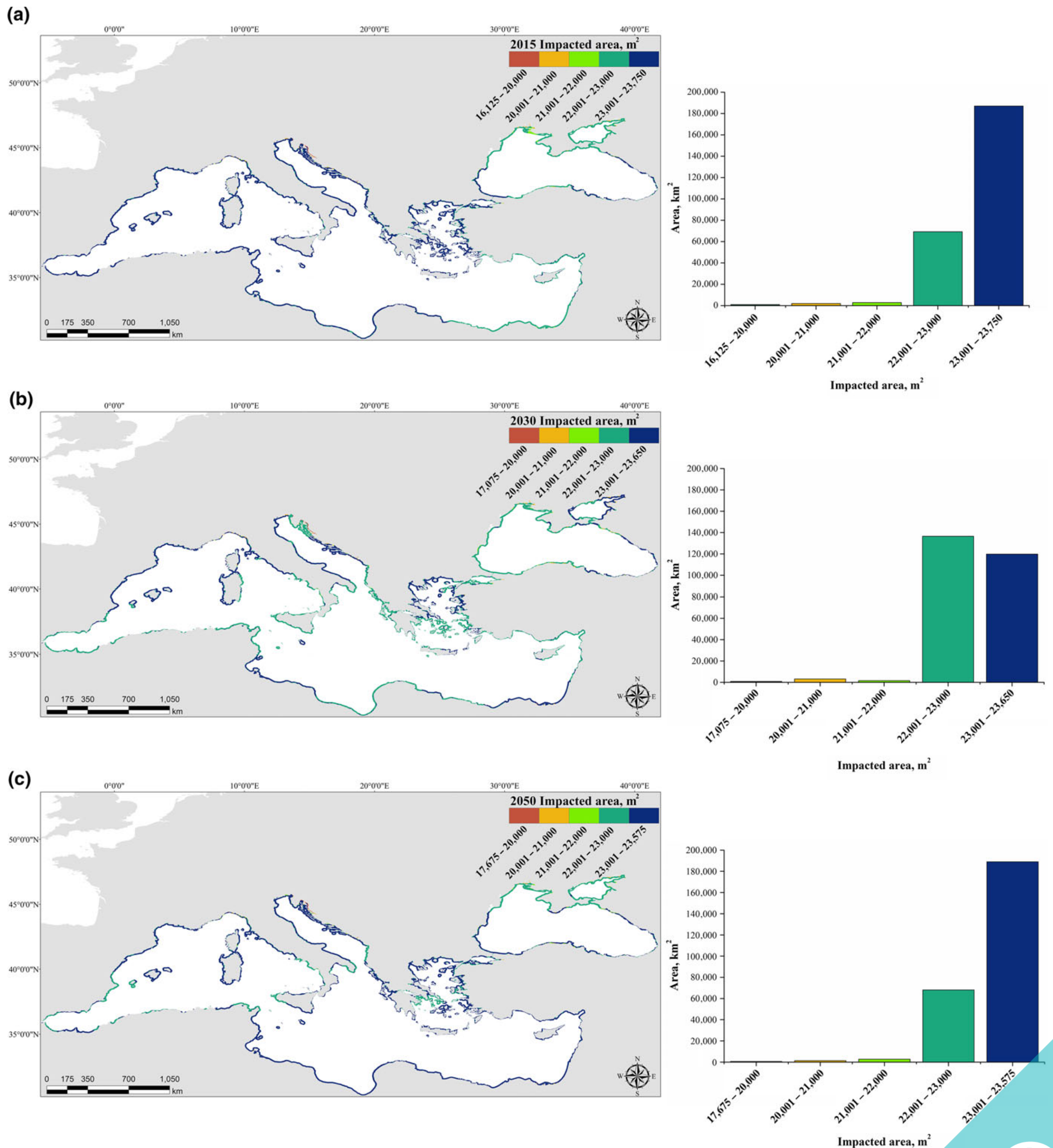

FIGURE 3 The impacted area (m^2; LOAD), from top to bottom, respectively, across 2015, 2030, and 2050. Five classes of impact are reported, respectively, in 2015: 16,125–20,000; 20,001–21,000; 21,001–22,000; 22,001–23,000; 23,001–23,750; in 2030: 17,075–20,000; 20,001–21,000; 21,001–22,000; 22,001–23,000; 23,001–23,650; in 2050: 17,675–20,000; 20,001–21,000; 21,001–22,000; 22,001–23,000; 23,001–23,575. Each histogram on the right side of the panel shows the number of km^2 within each impact class [Colour figure can be viewed at wileyonlinelibrary.com]

In the ascending region, there was no trade-off between environmental and commercial components, as reducing either would reduce the overall climate change effect. Conversely, in the descending region, there was a trade-off between environmental and commercial components, as reducing one would not necessarily reduce the overall impact. There appears to be a strong latitudinal signal in the distribution of the trade-off between commercial and environmental components across all oceanographic scenarios in 2015, with

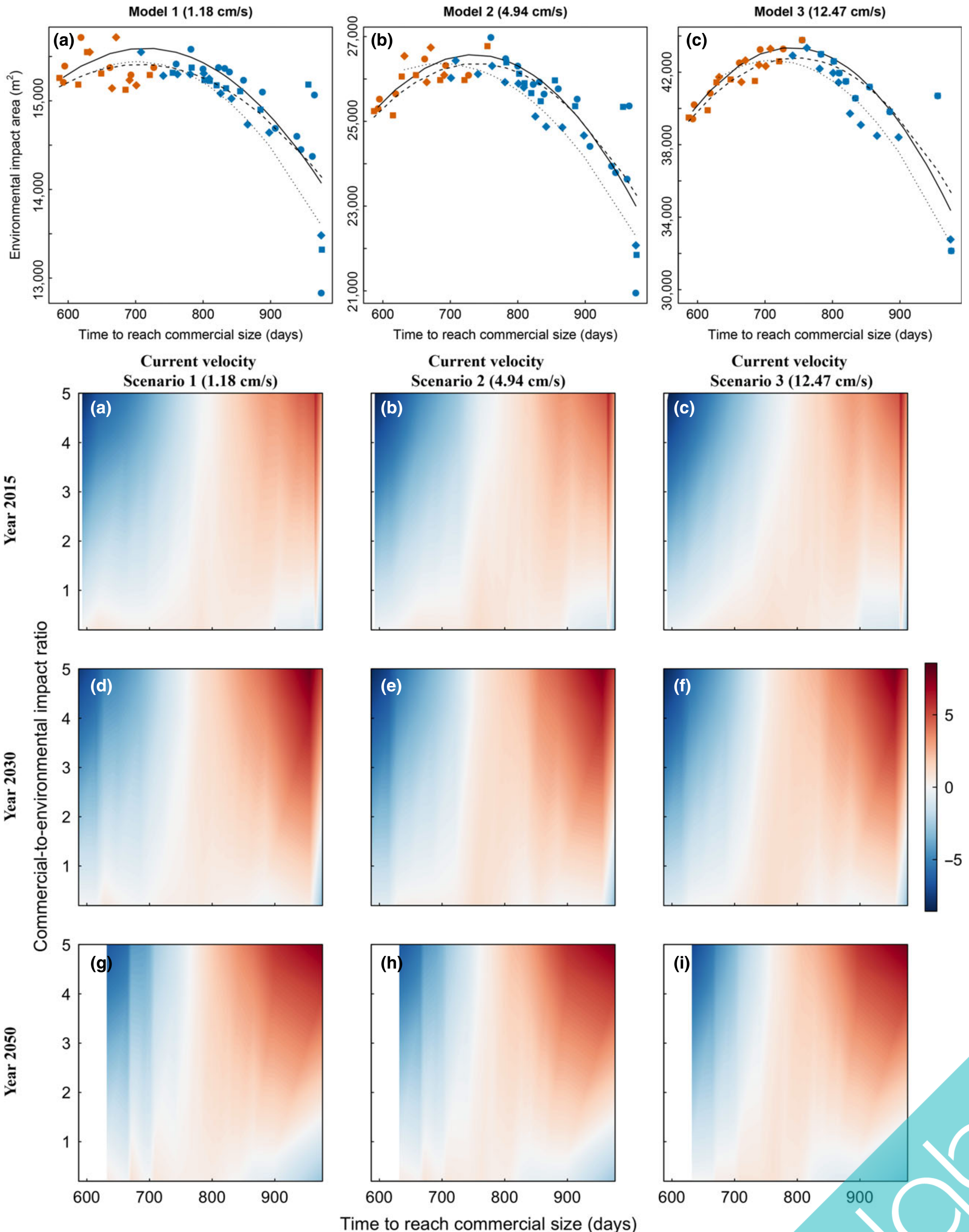

FIGURE 4 Optimization curves (upper panel). The optimization between environmental impacted area (m^2; LOAD) and time to reach commercial size (days; TIME) with Similar Average Temperature Regions (SATRs) under three different scenarios of current velocity (a = 1.18 cm/s, b = 4.94 cm/s, c = 12.47 cm/s). SATRs under a "no trade-off" condition are reported in red, SATRs in a "trade-off" condition are in blue. Different symbols refer to SATRs of each of the three time periods: circle = 2015, square = 2030, diamond = 2050. The model fits are coded based on year: solid line = 2014, dashed line = 2030, dotted line = 2050. Lower panel shows optimization trends among the three scenarios of current velocity and years 2015, 2030, and 2050 [Colour figure can be viewed at wileyonlinelibrary.com]

northern regions being dominated by a trade-off and southern regions by a lack of trade-off (Figure 5). However, this latitudinal signal decayed over time across all oceanographic scenarios, as trade-off and no trade-off regions become more interspersed in space (Figure 5). Additionally, although the first two oceanographic scenarios indicate a southern expansion of the trade-off regions, the third oceanographic scenario indicates a northern expansion of the no trade-off regions (Figure 5).

Although quantifying the commercial and environmental components of climate change separately across the Mediterranean Sea is an important first step, stakeholders require an integrated metric in order to facilitate spatial planning and management of aquaculture activities. We devised a measure of total impact (z_{total}) by summing z-scores of the commercial (z_C) and environmental (z_E) components: $z_{total} = z_C + a\ z_E$ (see Supporting information). Given the lack of information regarding the relative importance or valuation of commercial and environmental impacts, we then conducted an extensive sensitivity analysis to determine how different weightings of these two components would affect the total impact of climate change by varying the value of "a," a measure of commercial-to-environmental impact, from 0 to 5. Our sensitivity analysis revealed that the total impact of climate change on aquaculture is expected to increase over time across all oceanographic scenarios (Figure 4). Indeed, across all three oceanographic scenarios, the total impact increased over time for all commercial-to-environmental ratios. By 2050, only regions characterized by very low values of commercial component or very low commercial-to-environmental impact ratios would be characterized by low total impacts. Most of the regions, however, were characterized by intermediate to high total impact, depending on the commercial-to-environmental ratio (Figure 4). Hence, climate change will make the practice of aquaculture challenging by increasing both the frequency of trade-offs between commercial and environmental components across the Mediterranean and Black Sea and the total impact under most valuation scenarios (Figures 4 and 5; Supporting information Figures S8 and S9).

Overall, our results demonstrated that adopting an integrated framework that involve both environmental costs and benefits is necessary to anticipate vulnerabilities, reduce the risk of mismanagement and ensure the sustainability of human activities at sea under future climatic projections (Cochrane, De Young, Soto, & Bahri, 2009). Present results also suggest that optimizing aquaculture practices by minimizing total impact will become increasingly difficult under climate change for most oceanographic scenarios (Supporting information Table S5). Although we believe that the approach adopted and summarized in Figure 1 is sound, it is important to acknowledge that our findings should be interpreted with caution, as both the computational burden and the availability of site-specific data have set some limitations to its implementation in the study area.

The index LOAD is computationally much more expensive than TIME, as it requires the integration via Montecarlo simulation of the trajectories of 7×10^9 particles in a 2D domain, which took

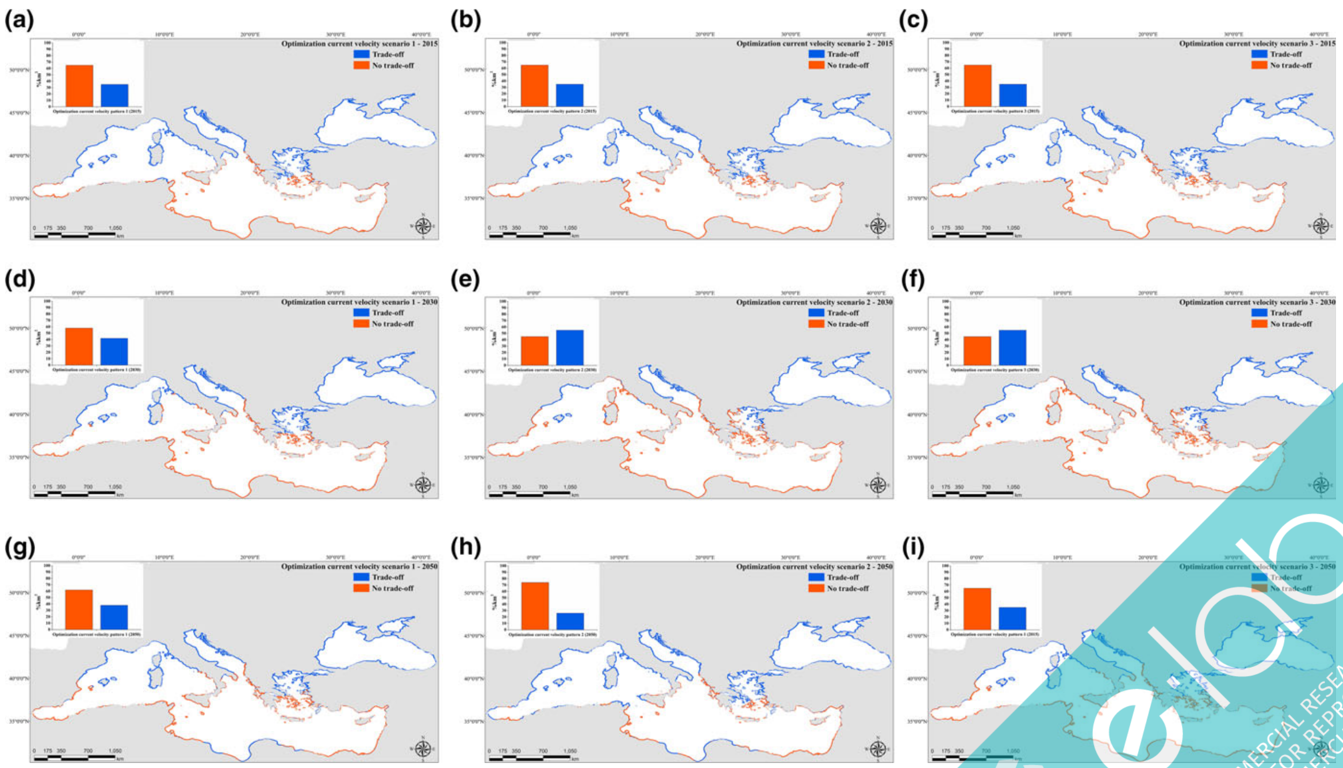

FIGURE 5 Optimization maps of the Mediterranean and Black Sea across three scenarios of current velocity (scenario 1: 1.18 cm/s; scenario 2: 4.94 cm/s; scenario 3: 12.47 cm/s) and years 2015, 2030, and 2050. Blue and red bars refer to the percentage of km^2 respectively under "trade-off" or "no trade-off" conditions [Colour figure can be viewed at wileyonlinelibrary.com]

approximately 126 hr on the available computational resource. Therefore, it would not be easy to run FiCIM at each grid point in order to assess a site-specific impact. Furthermore, such an approach requires site-specific hydrodynamic circulation data, although data from operational oceanography could have served the purpose for 2015 scenarios, projecting currents for the 2030 and 2050 would have been highly speculative. For this reason, we explored nine oceanographic scenarios, which are representative of the present current and depth distributions of fish farms. The results of our investigation (see also the Supporting information section) showed that both bathymetry and average current speed play a significant role in determining the actual impact. Furthermore, our findings also show (see Figure 4) that, in most SATRs, impact decreases as TIME increases, such that wherever an increase in temperature will shorten the grow-out phase, one can expect an increase in the moderately impacted benthic area. To this regard, we would like to point out that this area was defined on the basis of a threshold suggested by the literature, i.e., 1 g C m^{-1} day^{-1} (see also the Supporting information section), in keeping with a precautionary principle. In general, in the presence of similar local bathymetry, the higher the current speed, the larger the areas affected by moderate organic enrichment, although the cumulative value of organic material deposited *per* unit surface will decrease. On the other hand, at sites characterized by low hydrodynamic dispersion this area would shrink, but the deposition of organic matter in surface could reach much higher values, inducing a shift toward anaerobic degradation pathways. Therefore, proper site selection, based on site-specific data, will become even more relevant in the future. In the present study, we did not consider the effect of an increasing temperature on the degradation of the organic matter in surface sediment, which could further increase the impact on sediment biogeochemistry and, in particular, on the oxygen sediment demand. Therefore, the organic carbon flux, which was taken as an indicator of moderate impact, may have to be revised and likely lowered.

4 | DISCUSSION

This study demonstrated how climate change could cause detrimental effects on sustainability when TIME and LOAD are integrated as trade-off into the environmental component of sustainability. Here, the use of TIME or LOAD as sole indicators could lead to counterproductive management decisions and yield net negative results (Figures 2 and 3) (e.g., Sea-Level-Rise in wetland systems; Kirwan & Megonigal, 2013). Consistent with previous work (Poloczanska et al., 2013; Rutterford et al., 2015), our analysis showed that increasing temperatures due to climate change would produce a mean poleward shift in the environmental trade-offs. Additionally, the integration of these two indices (TIME and LOAD) of aquaculture components (environmental cost and benefits) and downscaling to local conditions (e.g., current velocity) revealed strong differences in the spatial distribution of the trade-offs over time, with spatial variability increasing over time from 2015 to 2050. Since the Mediterranean and Black Sea Exclusive Economic Zones (EEZs) will experience distinct trade-offs in space and time (Supporting information Figures S8 and S9), management strategies must be local and adaptive in order to minimize total impact (FAO, 2016). Such spatially explicit and multipronged information is critical to develop, promote and encourage for cooperation between knowledge producers (scientists) and knowledge users (policy-makers) representing a solid knowledge baseline in order to tailor future effective local sustainable management measures in aquaculture-dependent countries.

To this regard, the approach here proposed could be used in an adaptive management framework, with innovation in cage management aimed at lowering its environmental impact and improving its performances can be easily taken into account by changing model parameters, with respect to the estimates used in the present application. For example, as regard feed performance and feeding management (e.g., lower FCR and differences in feed elemental composition) can be accounted for by adjusting the parameters reported in Supporting information Table S3, while higher buoyancy by decreasing the settling velocity of feed particles, parameter w_{fo} in Supporting information Table S4.

Therefore, present approach can provide a sound environmental baseline for constructing integrated models which allows one to explore socioeconomic future scenarios of (a) the industry development, (b) the markets' prices adaptive replies to the climate change, and (c) the growing seafood proteins demands. This will allow to build proactive models for a sustainable aquaculture (Chavanne et al., 2016; Sarà, Mangano et al., 2018).

Thus, policy and management measures must be addressed with spatial and temporal scales matching the values and issues of concern as suggested for other human activities (Muñoz, Farrell, Heath, & Neff, 2015; Paterson, Kumar, Taylor, & Lima, 2015); however, they are only rarely applied (Creighton, Hobday, Lockwood, & Pecl, 2016; Lu, Nakicenovic, Visbeck, & Stevance, 2015).

Although our analysis focused on a single species, this mechanistic approach can easily be extended to other aquaculture species, as it exploits the power of species-specific biological traits (sensu Courchamp et al., 2015). Extending our framework to other species would help generate predictions about the distribution of multispecies trade-offs in space and time as well as identify winners versus losers in the face of climate change. The generation of freely available and updated multispecies trade-off maps will represent an useful tool to help researchers track progress in plugging knowledge gaps and drive decision-makers, stakeholders and public opinion in developing adaptation and mitigation solutions at biologically relevant spatio-temporal scales. The seabass is thought to be the best candidate for Northern Europe aquaculture although there are no biological-trait databases to date to corroborate it; this remains more a working rather than data-driven hypothesis.

Aquaculture is expected to become potentially crucial in meeting the world's seafood demand since catches of most wild commercial fisheries are at or beyond their maximum sustainable yield (FAO, 2016, ICSU & ISSC, 2015) with consequent alteration of seabed integrity (Mangano, Bottari et al., 2017). However, our analysis shows that climate change may fundamentally limit the ability of aquaculture to satisfy the future seafood needs of a growing human population.

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AUTHOR CONTRIBUTIONS

G.S., T.C.G., M.C.M., and R.P. conceived the idea, addressed the objective of analyses and equally led the writing; G.S., S.M., A.M., R.P. provided funds, hardware and software facilities; G.S. carried out the DEB predictive modeling; D.B. carried out the FICIM modeling; E.M.D.P. carried out the mapping activity; and M.C.M. performed the systematic review of literature.

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SUPPORTING INFORMATION

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