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ClimeGreAq: A software-based DSS for the climate change adaptation of Greek aquaculture

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ABSTRACT

Climate change poses increasing challenges to aquaculture, resulting in the need to develop appropriate tools to assess these challenges and support decision-making. We present ClimeGreAq, a software-based Decision Support System (DSS) co-created with stakeholders to support the adaptation of Greek aquaculture to climate change. The DSS is based on an integrated modeling approach which links a biological and an economic model in order to simulate the effects of climate drivers on Greek aquaculture in a spatially heterogeneous manner. The tool may be used by stakeholders including farmers, producer organizations, regional administrations and national authorities to support decision-making on questions ranging from selecting appropriate farming locations, to designating zones for aquaculture activities, to developing national climate adaptation plans. Along with a description of the DSS design process, its structure, and the constituent models, key results are presented relating to stakeholder involvement, the user interface, and several application examples.

1. Introduction

Food production systems are increasingly under pressure at a global scale from threats stemming from climate change. Marine aquaculture, in particular, faces special challenges due to the nature of the activity, which allows little control over environmental conditions at the rearing sites. This may relate to threats regarding the biology of the farmed species, such as reduced growth and survivability, but it can also include financial implications for individual farms like increases in the various costs which, in turn, lead to lower profitability. In fact, it has been postulated that climate change may have profound implications for aquaculture production, the livelihoods of its associated communities, and consequently for national economies (Brander et al., 2018; Rosa et al., 2012). A case in point is Greece, one of the main producers of European seabass (*Dicentrarchus labrax*) and gilthead sea bream (*Sparus aurata*) in Europe, representing over 60% of the total European production (FEAP, 2017). These species are predominantly farmed in marine cages, which therefore renders marine aquaculture the focus of this article. Moreover, aquaculture products rank amongst the most important agricultural exports for Greece and, thus, make a significant contribution to the national economy (FGM, 2019).

It is therefore crucially important that potential threats as well as opportunities arising from climate change are assessed and adaptation actions are taken where needed. However, assessing the effects of climate change on aquaculture production is rarely self-intuitive for decision makers. This is due to the multitude of environmental drivers associated with climate change (temperature, acidification, extreme events, shifts in ocean circulation, and Harmful Algal Blooms (HABs) among others), their complex interactions with the production systems as well as among them, and the knowledge gaps regarding the biological responses of farmed fish to these drivers (Dabbadie et al., 2018; Wells et al., 2020). As a result, developing strategies to adapt to climate change remains cumbersome for decision makers. One option to support and facilitate decision-making in this context is the development of appropriate tools that can aid decision-making. These tools, which are referred to as Decision Support Systems (DSS), must be able to provide supporting information to decision makers so that management and policy makers can take strategic decisions to promote sustainability of the industry in the coming decades. In addition, these tools must achieve a balance between the information they contain and user-friendliness to

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make them easily accessible to decision-makers (Wenkel et al., 2013). In this paper, we present such a DSS (ClimeGreAq) developed to support decision-making for Greek marine finfish aquaculture under climate change.

In general, DSS are information systems designed to facilitate decision-making in relation to complex problems. Their main functionality lies in allowing users to test specific management objectives by comparing alternative states of their system. Recent achievements in computer science have spurred the development of novel, interactive, software-based systems (Capalbo et al., 2017; Holzworth et al., 2015) with some of them focusing on impacts of environmental changes on food production (Cobo et al., 2019; Hermawan and Syafrani, 2015; Sturm et al., 2018; Wätzold et al., 2016). With respect to the specific challenge of climate change, several DSS have also been developed, ranging from risk assessments using scenario-based approaches (Han et al., 2017; Lieske, 2015; Schweizer, 2019) to more sophisticated interactive tools that tackle issues related to the management of water and energy resources, land use, and biodiversity (Kašpar et al., 2018; Kazak, 2018; Pierleoni et al., 2014; Ziaja, 2019). In addition, long-term environmental impacts have been simulated for pond aquaculture with the objective of establishing a comprehensive background for the subsequent development of a DSS (Varga et al., 2020). However, the connection between climate change and aquaculture in a DSS form remains elusive.

Overall, decision support systems in aquaculture are scarce despite the substantial number of such systems produced in other domains. Nevertheless, a few DSS exist in aquaculture which are increasingly adopting software-based approaches in an effort to tackle the highly complex and multifactorial nature of farming and its interactions with the natural environment (Casini et al., 2015). For instance, the inclusion of Geographical Information Systems in tools that support decisions in fish farming has been suggested (Falconer et al., 2018), while other technologies such as Particle Swarm Optimization techniques have already been developed for other applications (Cobo et al., 2019). Other approaches include Multi-Criteria Decision-Making methodologies as in the case of a gilthead seabream DSS for feeding strategies (Luna et al., 2019) and the development of DSS for optimizing site selection according to the prevailing environmental conditions (Halide et al., 2009; Nobre et al., 2009; Stelzenmüller et al., 2017). Yet, as has been highlighted by Mathisen et al. (2016), most of these efforts fail to capture the complexities required for decision-making in aquaculture since they are generally focused on a small number of drivers and species. Moreover, there are significant gaps related to decision support in a climate change context as none of the existing DSS for aquaculture deals specifically with future projections of climate drivers.

Responding to the need to develop tools for informed management in aquaculture under a changing climate, this article describes ClimeGreAq, a software-based DSS for Greek aquaculture. The aim of ClimeGreAq is to simulate and visualize biological effects of climate change on typical farmed fish species and their repercussions on farm economic indicators for Greek aquaculture under different climate scenarios and over distinct future periods extending up to the year 2050. This includes effects of climate drivers such as temperature and wind velocity in several areas throughout Greece, which allows the consideration of spatial heterogeneities across the country caused by differences in the projected climate conditions. Moreover, in addition to simulating and visualizing climate change impacts, the DSS includes an optimization module for some farming parameters. By doing so, it allows its users to investigate alternative what-if scenarios in a changing climate and support strategic decisions based on the relative differences between the possible outcomes. In order to consider links between biological and economic impacts, a bio-economic modeling procedure (Drechsler, 2020) was adopted for its development following established practices for investigating the effects of changing environmental conditions in aquaculture systems (Besson et al., 2016; Cobo et al., 2019).

The DSS was developed in collaboration with stakeholders in the context of the EU-project (Horizon, 2020) Climefish (https://climefish.eu/) following the co-creation suggestions of the European Commission (European Commission, 2014). The co-creation approach aims at increasing the relevance of the generated products for their users, in this case, Greek aquaculture stakeholders such as farmers, producer organizations as well as regional and national authorities. In that way, the DSS may be useful for supporting decisions at small scales such as the management of farms in terms of selecting appropriate seeding schemes and farming locations, but also at medium and larger scales by aiding policy makers in designating or modifying aquaculture activity zones or in developing climate adaptation plans at a national level. For this reason, the implementation of ClimeGreAq occurred in stages, between which stakeholder feedback was gathered and taken into consideration for its further development.

A prototype version of the DSS, produced in the early stages of the project, has already been presented in Stavrakidis-Zachou et al. (2018). Since then, substantial changes, additions, and refinements have been implemented. The software-based DSS presented in this article is the final version of the ClimeFish DSS for aquaculture stakeholders in Greece. It contains all the updates and new functions that have been implemented into the software and particularly the stakeholder suggestions that emerged during the co-creation process. Specifically, compared to the earliest version presented in Stavrakidis-Zachou et al. (2018), the tool contains improved biological forecasting, in terms of key biological parameters such as fish growth and feed consumption, for the 2020–2050 period. The forecasting has been obtained using downscaled climate projections at a higher spatial resolution than before. Moreover, the spatial extent of the analysis is enlarged from pilot regions to the entire country, while effects of extreme weather events such as heatwaves and storms on fish growth and biomass production are also incorporated additionally to those of temperature. In terms of further methodological advancement, an optimization module has been implemented. Moreover, the tool includes an additional species, a risk assessment, updated maps and other visualizations, and finally, secondary windows and info-boxes for user orientation. The risk assessment is ignored in the following as it is based on a different methodology and was included in the software to provide stakeholders with one single platform where they could access all ClimeFish tools (further information about the risk assessment can be found in the manual and in the Case Study description of the ClimeFish toolbox (http://136.144.228.39:8080/climefish).

2. Methods

2.1. Process of software design and experimental testing

ClimeGreAq was developed applying a co-creation approach, which implies close interactions between scientists and stakeholders throughout the different stages of DSS development. As highlighted by McIntosh et al. (2011), engaging stakeholders as early as possible in a co-creation process is crucial for ensuring the relevance of the generated tools for the users as well as their longevity beyond a project's lifetime. Regular meetings with stakeholders are necessary to present the DSS idea as well as preliminary and final results. The purpose of such meetings is to gather feedback for the improvement of the DSS in terms of relevance of proposed parameters, adequacy for addressing the problem of climate change impacts on Greek aquaculture, user-friendliness, and model validation. This feedback shall then be taken into account in the further development of the DSS and the underlying model. Fig. 1 illustrates this process.

2.2. Overview of the structure

ClimeGreAq utilizes biological and economic information to simulate and visualize the effects of selected climate drivers on Greek aquaculture production. ClimeGreAq differentiates between nine Greek

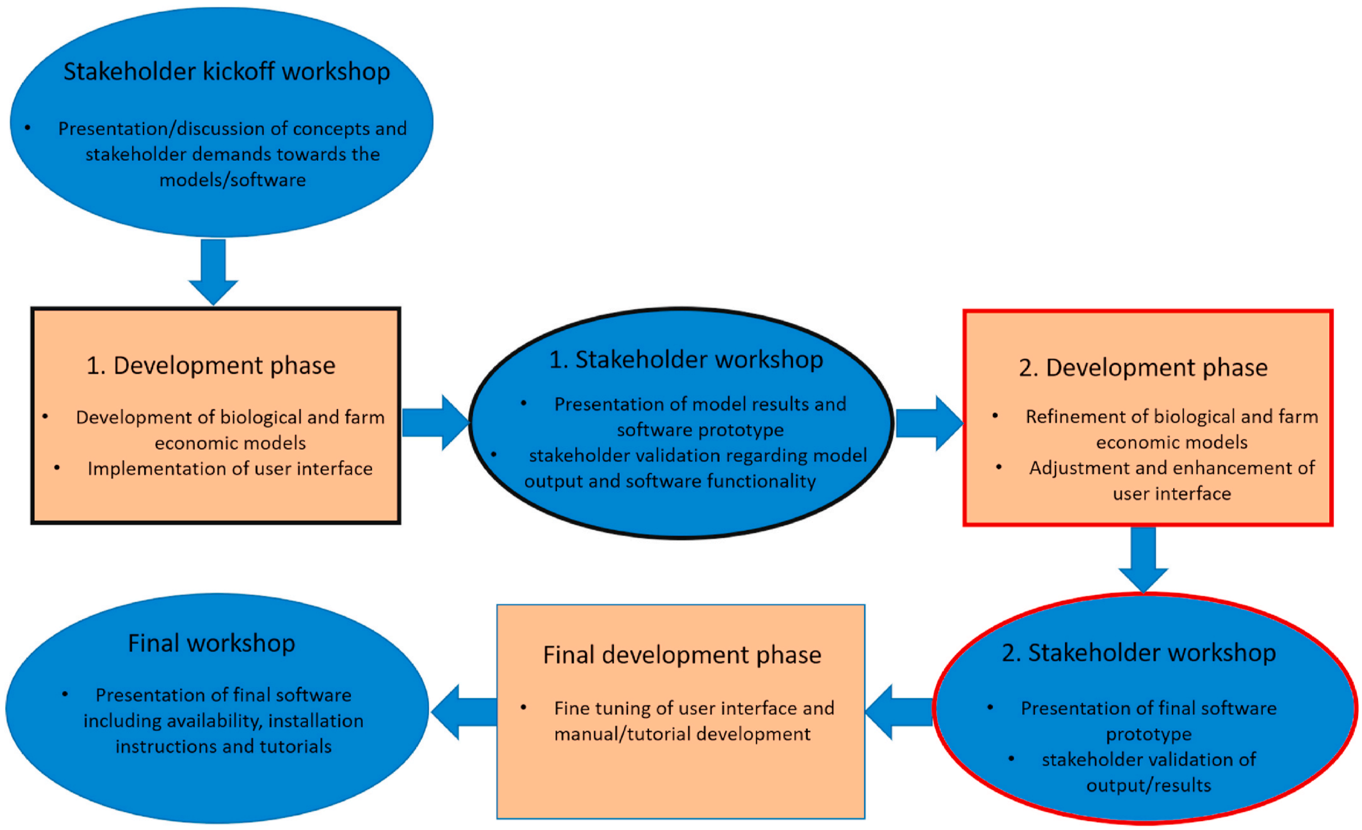

Fig. 1. The co-creation process followed for the development of ClimeGreAq.

regions and considers for each region inshore and offshore production, resulting in eighteen representative farms. Its core structure is a coupled biological and farm economic model. The biological model is integrated in the DSS through a local MySQL database while the farm economic model is implemented into the software. In addition, the interactions of these components with the user occur via a user interface (Fig. 2).

The decision support capacity of the software lies in allowing users to create and compare a wide range of alternative future climate change and management scenarios. To accomplish that, a model farm approach was adopted which targets representative farms throughout the Greek territory as the basis of the analysis. Such an approach appears to have increasing relevance for aquaculture as indicated by current research (Besson et al., 2016; Cobo et al., 2019; Piedecausa et al., 2010).

For the various climate scenarios, the biological model for the model farm simulates a production cycle for a group of fish and reports several parameters of interest such as time to market size, feed consumption, and biomass at a harvest size specified by the user. Subsequently, the farm economic model uses the output of the biological component as well as other economic data input to estimate relevant farm economic parameters. Due to considerable computational time, the biological simulations are not done by the software but comprise a selection of precomputed scenarios which are stored in the local database. All other computations happen in real time.

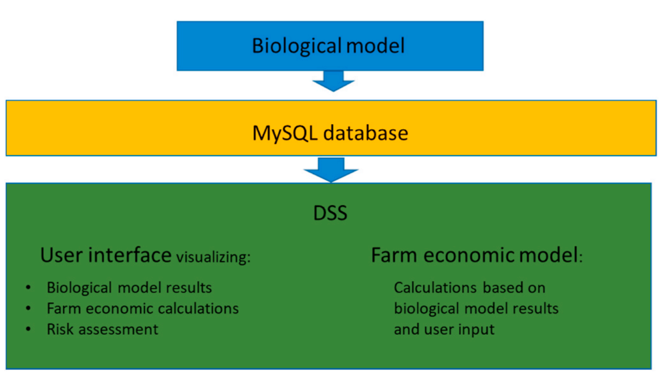

Fig. 2. The structure of ClimeGreAq.

2.3. Biological model and simulations

This section provides an overview of the biological model including the overall framework it is based on and the main linkages among its components as well as a description of the data and scenarios used for the simulations. For a detailed description of the biological model and the development process, the parameters and the formulae used in the simulations we refer to Stavrakidis-Zachou et al. (2021) and the respective supplemental electronic material.

2.3.1. The DEB model

The biological model is based on Dynamic Energy Budget (DEB) theory. Via the DEB framework, the bioenergetics of an individual fish can be described as a function of temperature and food availability by following certain rules for the uptake of energy and its utilization by the organism (Kooijman, 2010). According to this framework, the weight of an individual comprises of structure, reserve, and in the case of adults also of reproductive biomass. The various metabolic processes are fueled by mobilized reserve which is formed during the process of assimilation. During feeding, part of the food consumed by the organism is assimilated into reserve, while the rest is lost through defecation. At any given time, a fraction of the mobilized reserve (κ) is used for growth and the rest $(1-\kappa)$ for maturation or reproduction purposes. Specifically, growth is incorporated as increase in the structural biomass (structure) of the organism after maintenance costs have been paid. On the other hand, maturation represents investments in development (with life stage transitions occurring at specific maturation thresholds) and in the case of reproducing adults, the production of gonads after subtraction of the respective maintenance costs. All these processes are governed by temperature, with the temperature effect on the various physiological rates being quantified via the Arrhenius relationship in the DEB context (Aguera et al., 2015; Kooijman, 2010; Stavrakidis-Zachou et al., 2019).

In this framework, changes in measurable quantities such as weight and feed consumption for a single fish can be predicted as a function of temperature and food availability which can be provided as inputs. Moreover, this process can be repeated for many individuals, thus extrapolating the output to the population level. An overview of the biological model scheme and the general method including the inputs and outputs of the model is provided in Fig. 3.

DEB models were developed for two species, the E. seabass (*Dicentrarchus labrax*) and the meagre (*Argyrosomus regius*), and were validated against production data from farms. The parametrization of the models was done according to the procedure described in Marques et al. (2019), using information from published literature as well as experimental work conducted at the Hellenic Center for Marine Research (HCMR). For model validation, eight datasets (growth, measured as the evolution of weight over time, and feed consumption) from Greek farms at various locations were used. After simulating the temperature and feeding conditions at those locations, the model predictions were compared with the farm data. A close overlap of model predictions with farm observations indicated that growth was captured accurately by the model while there was a slight tendency towards underestimating feed consumption. Specifically, in all cases the weight and feed consumption values predicted by the model did not deviate more than 20% from the observed data (coefficient of variation < 0.2). Further details on the parameterization and validation of the two models can be found in previous publications (Stavrakidis-Zachou et al., 2019, 2021).

2.3.2. Simulations

Simulations were performed for nine Greek regions and for three time periods denoting short-, mid-, and long-term effects (2015–25, 2025–35, and 2045–55) under the IPCC (Intergovernmental Panel on Climate Change) climate scenarios RCP4.5 and RCP8.5. For these scenarios, the projections of temperature and wind velocity were forced on a group of fish to simulate a three year production cycle at farm level. The environmental variables comprised of downscaled 10 × 10 km projections of the Global Climate Model ICHEC-EC-EARTH via the coupled POLCOM-ERSEM ecosystem model (Proudman Oceanographic Laboratory Coastal Ocean Modeling System and the Plymouth Marine Laboratory European Regional Seas Ecosystem Model). In addition, for each region two farms were considered, one inshore and one offshore. This was done to assess effects on exposed locations since offshore aquaculture has been recognized to have great potential for the future of Mediterranean finfish aquaculture (Porporato et al., 2019). Furthermore, adapted seeding planning was incorporated into the simulations via the inclusion of three seeding months (March, June, September). Predictions of growth (in terms of the time needed to reach a specified market size), the number of fish, the total biomass, the cumulative feed consumption and the feed conversion ratio (FCR) were then computed for the different climate and management scenarios; the latter referring to the various production options such as site selection, and seeding time and size. Moreover, a preliminary assessment was done to determine the sensitivity of simulation outputs, such as growth, to climate model uncertainties. Specifically, bootstrap samples of temperature and wind velocity time-series were generated within each time period as described in Stavrakidis-Zachou et al. (2021), and were used to run simulations for an individual fish. Overall, climate uncertainty produced little variability in all considered climate scenarios, as indicated by the narrow width of the grey shaded area (coefficient of variation < 0.05 for this simulation) (Fig. 4).

Our model focuses on temperature as the main climate driver. Modeling other drivers explicitly would have been difficult due to a lack of supporting data on environmental projections, inadequate spatial resolutions, and significant knowledge gaps regarding the biological species-specific effects of other drivers. However, in line with recommendations from stakeholders who emphasized the need to include additional drivers, an indirect approach was followed to incorporate effects of winds and extremely high temperatures (heatwaves) on

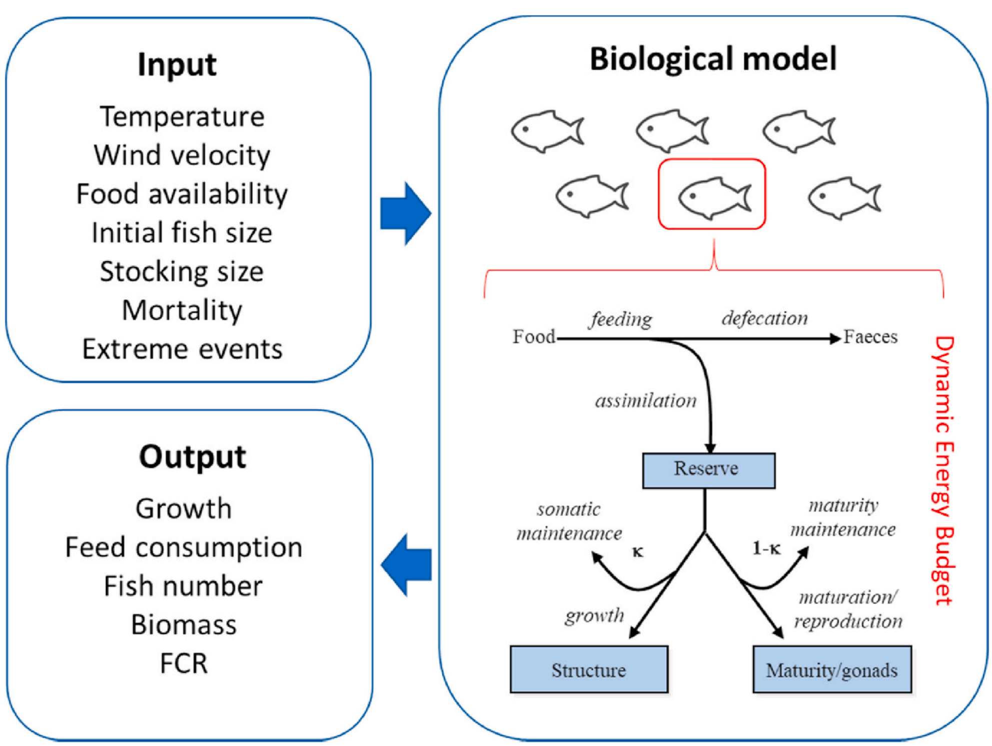

Fig. 3. Main scheme of the biological model, including the list of inputs and outputs.

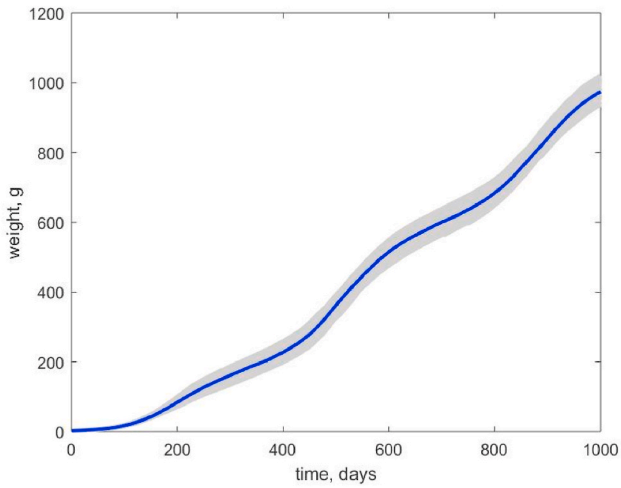

Fig. 4. Simulated weight over time for an individual fish (species: E. seabass). The grey shaded area indicates climate projection uncertainty as estimated from simulations using bootstrap samples (n = 50) for temperature and wind velocity projections. The blue line denotes the average among simulations.

feeding and mortality. The model considered the effects of wind on feed consumption and, therefore, on growth by incorporating non-feeding days when wind velocity exceeded predefined thresholds. This was done to simulate restricted farm accessibility or adverse weather conditions that hinder feeding operations (e.g., high waves). Moreover, extreme events such as storms and heatwaves were included as additional causes of mortality. The rationale was that storms can damage the cages and cause equipment failure, thus leading to escapee events, while prolonged high temperatures are tied to disease outbursts, both of which are incorporated as mortality losses in aquaculture terms. Specifically, changes in the number of fish during the simulations were calculated as

$$\frac{dN}{dt} = -(\mu + \mu_T + \mu_S)N$$

with N being the number of fish, μ a background mortality rate, μ_T and μ_S mortality rates related to storms and heatwaves, respectively. Both μ_T and μ_S were set to zero during the production cycle, except for the days extreme events occurred at specified wind and temperature thresholds (Stavrakidis-Zachou et al., 2021). Quantitative information on mortality losses from storms and heatwaves is currently not available on the spatial scale required by the software and the perception of the relevance of these risks may be highly subjective. Therefore, we leave information on all mortality values including μ_T and μ_S as user input in ClimeGreAq to allow further experimentation according to the users' perception.

2.4. Farm economic model

The farm economic model has been implemented as an add-on to the biological model and its core function is to estimate relevant business parameters of a single (model) farm. To do so, it uses the outputs of the biological model and user-defined economic input variables to derive the main costs and the profit for the farm under various climate and management scenarios. Table 1 contains the input variables needed for the operation of the model along with typical values for the various prices and costs. These values have been compiled in collaboration with the Federation of Greek Maricultures (FGM). It should be noted, however, that these values do not represent official statistics for the industry and serve solely for DSS user orientation. The values may vary considerably depending on farm characteristics and location. The farm economic model has been developed by Syntesa (Syntesa, 2020).

For simplicity, it is assumed that all prices provided in Table 1 remain unchanged during the production period. Based on the user input for these variables, the total costs per production cycle for feed, juveniles, labor, depreciation, and other costs are then calculated according to equations (1)–(5) (Table 2).

The rationale for selecting these variables for the farm economic calculations is that they follow the general cost structure for aquaculture. Feed and feeding represent the most important operational costs for the industry (Baki and Yücel, 2017) and are followed by costs related to wages and the number of hired personnel, while maintenance costs and the initial expenses for obtaining stock (juveniles) or equipment also comprise a significant portion of the budget (Koçak and Tathdil, 2004). For ClimeGreAq, all these variables are user defined and therefore allow great flexibility for testing alternative economic scenarios. The inclusion of 'other costs' further contributes to that by allowing the inclusion of costs like maintenance, repairs, fuel consumption and others that may have not been accounted for.

In aquaculture, the production cycle is relatively long compared to other forms of farming and it exceeds 1.5 years for most Mediterranean species. Moreover, farmers often resort to taking loans to support the initial installation of specialized farming infrastructures as well as for maintaining them. Consequently, debt is an important factor for the industry since costs tend to accumulate during the production cycle until revenue is generated by selling the fish after the harvest (Engle, 2010). For this reason, an accumulated debt has been incorporated into the

Table 1
Description of input variables for the economic model. Typical values according to FGM cost analysis for Greece.

Variable	Unit	Description	Input type	Typical value
$Price_{feed}$	€/kg	Feed price	User	1.15
$Price_{juveniles}$	€	Price per individual juvenile	User	0.23
$Price_{labor}$	€/day	Cost for total labor	User	149.64[a]
$Costs_{other}$	€/day	Maintenance and other operational costs	User	47.5
$Costs_{depreciation}$	€/day	Cost of depreciation for equipment, buildings, storage, and vessels	User	8.72
$Price_{interest\ rate}$	%	The daily interest rate imposed by banks	User	2
$Price_{sales}$	€/kg	Ex Works (seller's price before transport costs) sales price	User	6.44
Market size	G	Desired fish size for harvesting	User	–
Seeding population	#	Number of juveniles purchased	User	–
Feed consumption	kg	Total feed consumed during the production cycle	Biological model	–
Production time	Days	Time required for fish to reach market size	Biological model	–
Production	kg	Total biomass of fish harvested	Biological model	–

[a] Value for 4 persons involved in the production.

Table 2
Equation list of the economic model.

$Feed\ Costs = Feed\ consumption \times Price_{feed}$	(1)
$Juveniles\ Costs = Number\ of\ juveniles \times Price_{juveniles}$	(2)
$Labor\ Costs = Production\ days \times Price_{labor}$	(3)
$Other\ Costs = Production\ days \times Costs_{other}$	(4)
$Depreciations\ Costs = Production\ days \times Costs_{depreciation}$	(5)
$Accumulated\ debt_t = Accumulated\ debt_{t-1} + Feed\ Costs_t + Juveniles\ Costs_t + Labor\ Costs_t + Other\ Costs_t + Price_{interest\ rate} \times Accumulated\ debt_{t-1}$	(6)
$Total\ Costs = Feed\ costs + Juveniles\ Costs + Labor\ Costs + Other\ Costs + Depreciations\ Costs + Interest$	(7)
$Income = Production \times Price_{sales}$	(8)
$Profit = Income - Total\ Costs$	(9)

economic model (equation (6)) using equations (1)–(5) which is then used for the calculation of the bank interest as $Price_{interest\ rate}$ x *Accumulated debt.* It is assumed that all costs during production are financed by a credit, which holds for most small and medium-sized companies. Therefore, the accumulated debt for a given production period equals the sum of the current production costs, the debt of the previous period, and the bank interest of that debt. However, the bank interest can be set to zero by the ClimeGreAq user.

Finally, based on equations (1)–(6), the total costs and the generated income can be calculated which allow the derivation of the total profit for the farm for the selected scenario (equations (7)–(9)).

2.5. Optimization

A numerical optimization, combining results of the biological model with resulting economic predictions and user market goals enables users to compute optimal seeding schemes. The numerical optimization calculates for a given climate scenario, farm setting, mortalities and production goals all combinations of possible seeding schemes. The optimization calculates the total amount of fish to seed based on the targeted production, the requested market size and the mortality function. The different possible seeding schemes are calculated by distributing the total amount of seeded fish to the three possible seeding months, permuting the distribution and changing the number of seeded fish per seeding month in steps relevant for fish farming (i.e. 50,000 individuals) while keeping the total number per seeding scheme constant. For example, for a total amount of 900,000 seeded fish needed, the different seeding schemes would be all combinations of distributing the total amount of seeded fish in steps of 50,000 individuals to the three seeding months:

Comparing total feed and time to market size for all these options, the optimization minimizes the sum of these two parameters. The resulting optimal seeding scheme provides for the given parameters the minimum combination of total feed and total time to market size.

3. Results

3.1. Stakeholder involvement and its impact

Stakeholder involvement proved constructive not only for the initial development of ClimeGreAq but also for its refinement and validation throughout the project's timeframe. This was enabled by the multiple-loop approach which entailed developing ClimeGreAq and its underlying model in several iterations (Fig. 1). After each loop, the DSS, including the underlying model were presented to the stakeholders at a dedicated stakeholder meeting and their feedback was taken into account for its further development. Effort was made not only to include representatives from industry, administration and academia, but also to ensure a high overlap of participants between the meetings in order to have fruitful discussions and to receive consistent input during the project phases (Sturm et al., 2018).

First outlines of ClimeGreAq and the underlying model concepts were presented to the stakeholders along with a clear description of their capabilities and limitations at a kick-off stakeholder workshop only six months after the beginning of the project. The specific challenges for aquaculture under climate change were discussed as well as the features of the DSS to be developed.

Once the first round of biological simulations and the first version ClimeGreAq were developed, a first stakeholder workshop took place a year after the kick-off meeting. There, the preliminary version of the tool and the underlying models were presented along with a clear description of their capabilities and limitations. During that meeting, stakeholders provided valuable feedback which related to the content and output of models and the DSS as well as the appearance of the DSS. Specifically, key parameters were reconsidered and discarded or added accordingly. The stakeholder feedback and model validation crystallized the necessity to include the effects of additional climate drivers other than temperature in the biological model, eventually resulting in the incorporation of extreme events in the second loop simulations. Moreover, changes in visualization were discussed, the most notable being the suggestion to include a comparison window to allow simultaneous comparison of multiple scenarios.

The second stakeholder workshop took place a year later, once the agreed changes were incorporated into the software and the final biological simulations were completed. The updated tool was presented along with its new features, such as the comparison window and a preliminary optimization function, and the stakeholders were given the chance to test it themselves in designated computers. This generated further feedback comments and validation of the main outputs. The feedback mainly focused on appearance issues such as the form and position of graphs and axes or suggestions regarding the info-boxes and the user manual. These comments were implemented in the refinement of the software during the subsequent months.

The final version of ClimeGreAq as well as other decision support systems developed in ClimeFish were presented to stakeholders and academia at the final workshop of the ClimeFish-project.

3.2. User interface

The first window that users see when starting ClimeGreAq is the main user interface. It allows interaction with the various components of the DSS and is the gateway through which secondary windows and supporting information can be accessed (Fig. 5).

To investigate the different environmental, management and economic scenarios, the users must first select the climate scenario (RCP4.5 or RCP8.5), the species (E. seabass or meagre), the timeframe (short, mid, long), the location (inshore or offshore) and the region (R1-R9) of their choice from the respective drop-down menu. For the selection of the region, a map is provided which contains the positions of the model farms. Next, mortalities are assigned and seeding values (number of individuals) are given for the available seeding periods. Following this, the system retrieves the selected biological predictions from the database. The interface then enables the user to select different market sizes and insert values for the economic variables. This allows the calculation of the costs and profits of each market size in relation to the selected farm setting. The various outputs, including the total biomass, the time to market size, total feed consumption, costs and profits are computed and provided numerically but can also be visualized in graphs. The graphs can be exported as images for later use and comparisons.

The main menu also offers four additional options, seen on the top, which redirect the user to secondary windows. The first three options open new interactive windows while the last one, termed 'Background', opens a popup window with additional background information for the parameters used in the calculations and the constituent models.

As an additional option, by selecting the 'compare RCP/inshore – offshore' window the user can illustrate the modeled farm production results for all RCP/inshore – offshore combinations. This enables the user to compare the influence of the climate scenario and the farm setting while the other production parameters remain the same. Finally, the 'optimizing seeding' window enables the user to calculate the best seeding scenario for a chosen market size and production goal under different climate scenarios (Fig. 6).

For user orientation, info boxes with supporting information such as descriptions of the input and output variables and their units are incorporated into the software. These boxes appear once the user hovers above a selected variable and provide guidance on filling in the respective input values.

3.3. Application examples

In order to allow comparisons between many scenarios, we have considered multiple dimensions for the biological forecasting,

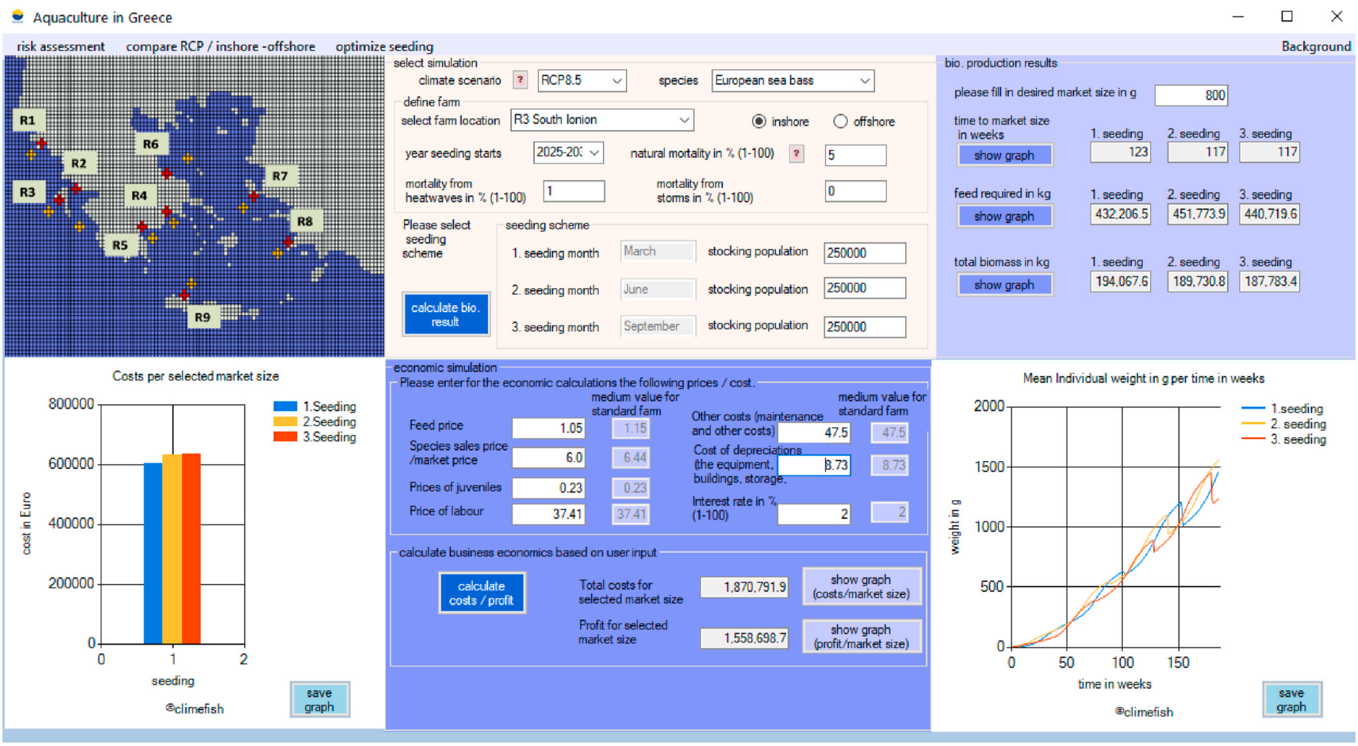

Fig. 5. The main user interface of ClimeGreAq. A map of all available regions is shown on the top left corner, and user input regarding the simulation parameters is given in the middle of the interface (top and center boxes). The biological forecast is illustrated on the right (top and bottom) while the bottom boxes show the economic predictions.

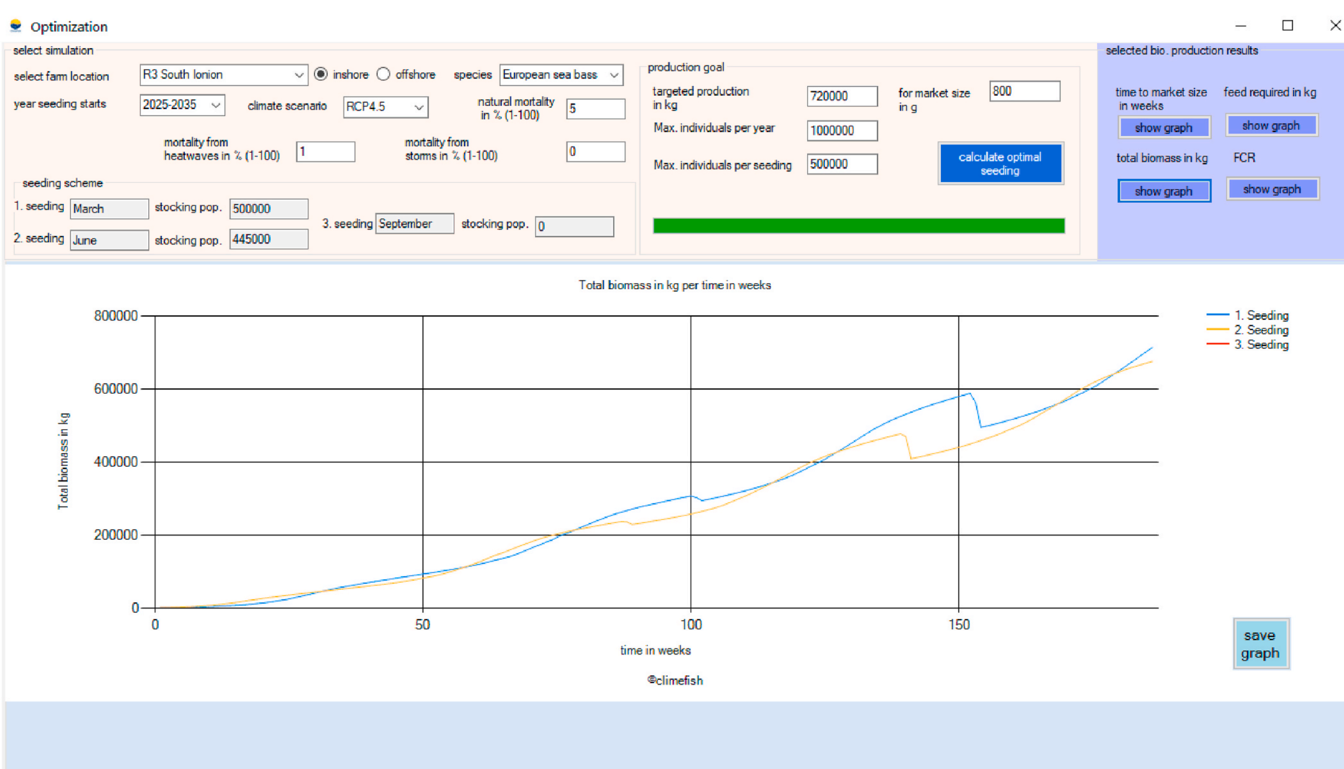

Fig. 6. The optimizing seeding window of ClimeGreAq.

incorporating two climate scenarios, nine regions, inshore and offshore locations, three seeding months, and two fish species. A comprehensive analysis of the effects of the simulated climate drivers (temperature and wind) on indicators such as the time required to reach common market sizes and the total biomass produced across these scenarios has been presented elsewhere (Stavrakidis-Zachou et al., 2021). In this section, we use specific examples to highlight the main capabilities of the software and its potential applications and also summarize results from the aforementioned study where appropriate in order to provide context.

The environmental profile of a simulation in terms of temperature and wind determines the growth performance for the fish. Consequently, parameters that affect the environmental profile such as the location of a farm, the climate scenario, the time period of the projection, and the region are expected to have effects on growth. From these effects, future shifts in variables such as time to market size and biomass production are among the most important for decision making since they provide information that may point to potential mitigation and adaptation measures. As shown in Fig. 7, ClimeGreAq can provide such critical information. In the example, and for the region and climate scenario considered, there appears to be a positive shift in growth as we move forwards in time with fish growing faster and reaching typical market sizes faster in the long term compared to now as a response to higher future temperatures.

In fact, the trend for time to market size to decrease in the future is consistent across all scenarios (Table 3). Specifically, Table 3 shows the relative change (%) in the time to market size (800 g) in the future compared to the present ($\frac{future - present}{present}$). It is evident, that fish will grow faster in the future since the relative change is negative across all cases. Moreover, meagre will benefit more compared to E. seabass as depicted by the higher absolute values while the trend will be more pronounced under the RCP8.5 compared to RCP4.5. In addition, for both species fish growth will be higher in the inshore farms compared to their offshore counterparts while differences will also be exhibited at different seeding months within each climate scenario. Finally, as reflected by the variability in the mean values, considerable differences will also appear between regions. In fact, it has been shown that even within the same climate scenario and seeding month, the time to market size may differ substantially among regions with fish in the southern (thus warmer) regions reaching the same size up to three months faster than in northern ones (Stavrakidis-Zachou et al., 2021).

In addition to evaluating shifts in individual growth, the effects of the considered climate drivers at the population level can also be analyzed. Due to the frequency and intensity of extreme events being different across the environmental scenarios, differences in the mortality levels, and therefore in the total biomass, can be derived. In turn, losses in biomass inevitably translate to losses in profit, which can be estimated and visualized in ClimeGreAq. An example of this can be found in Fig. 8, where the biomass production and profit of two farms that differ in their environmental profiles, are compared. For the selected comparison, the two regions differ latitudinally, with R1 being a northern and R9 a southern (warmer) region. As mentioned in the previous paragraph, southern regions typically exhibit higher individual growth as a direct positive effect of increased temperatures on fish metabolism. However, this gain is not depicted at the population level since the total biomass production is lower in R9 compared to R1. This is due to the higher frequency of heatwaves in the south, which cause substantial mortalities. As a result, the profitability of these farms is similarly affected, with the profits in R9 being lower than R1 and even negative for the March seeding. Furthermore, similar differences in biomass and profit could also be assessed within the same region for inshore and offshore locations via the secondary windows of the software (not shown). Since the environmental conditions between inshore and offshore locations differ not only in terms of the overall temperature profile but also regarding the frequency of extreme events, this provides a range of possible outcomes within a region which may provide useful information for evaluating the option of farm translocation as a potential adaptation measure.

Table 3
Relative change (%) between long- and short-term simulations in the time required for E.seabass and meagre to reach a typical market size (800 g). Values represent averages across the nine regions and are given for two climate scenarios (RCP4.5, RCP8.5), three seeding months (March, June, September), and two farm locations (inshore, offshore).

	seeding month	E. seabass		meagre	
		RCP4.5	RCP8.5	RCP4.5	RCP8.5
inshore	Mar	−2.0 ± 1.2	−3.3 ± 1.6	−3.9 ± 1.8	−4.7 ± 1.5
	Jun	−1.9 ± 1.3	−3.0 ± 1.3	−7.0 ± 1.9	−7.7 ± 1.7
	Sep	−3.7 ± 2.0	−4.2 ± 2.1	−5.4 ± 1.1	−7.7 ± 2.3
offshore	Mar	−1.8 ± 1.1	−3.1 ± 1.9	−3.1 ± 1.1	−3.6 ± 0.9
	Jun	−1.5 ± 0.7	−2.2 ± 1.2	−5.1 ± 2.4	−5.8 ± 1.3
	Sep	−0.27 ± 1.3	−3.9 ± 1.5	−6.4 ± 1.2	−8.5 ± 1.5

Indeed, with respect to inshore and offshore locations it has been shown that the frequency of heatwaves will be higher for the former compared to their offshore counterparts, but the opposite trend will hold for storms across all regions (Stavrakidis-Zachou et al., 2021). Moreover, heatwave frequency will progressively increase as we project forwards in the future while the frequency of storm events will not differ substantially compared to present levels. As a result, offshore farms will generally be less afflicted by extreme events in the future and will

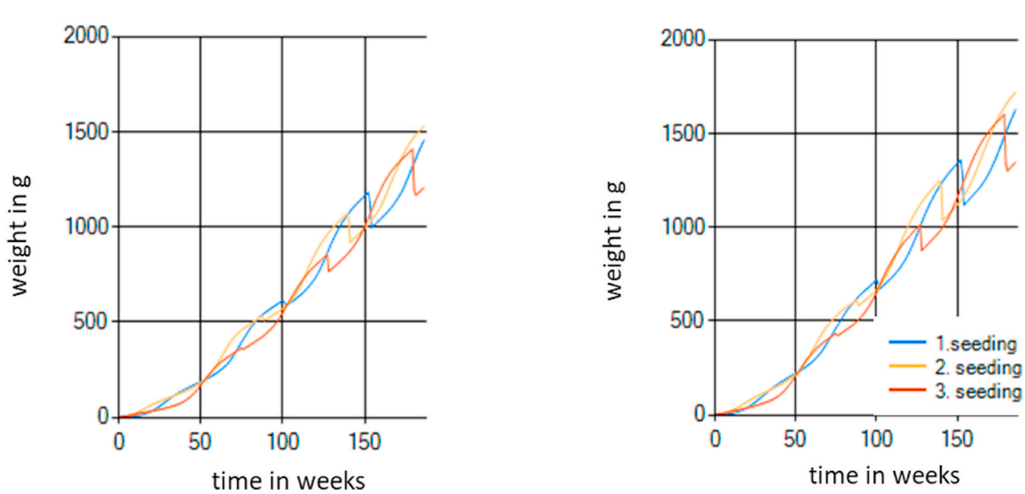

Fig. 7. Growth of E. seabass in the short (left) and long (right) term (scenario: region R1; inshore, RCP85; E. seabass). Colors denote the different seeding months (blue: March; orange: June; red: September).

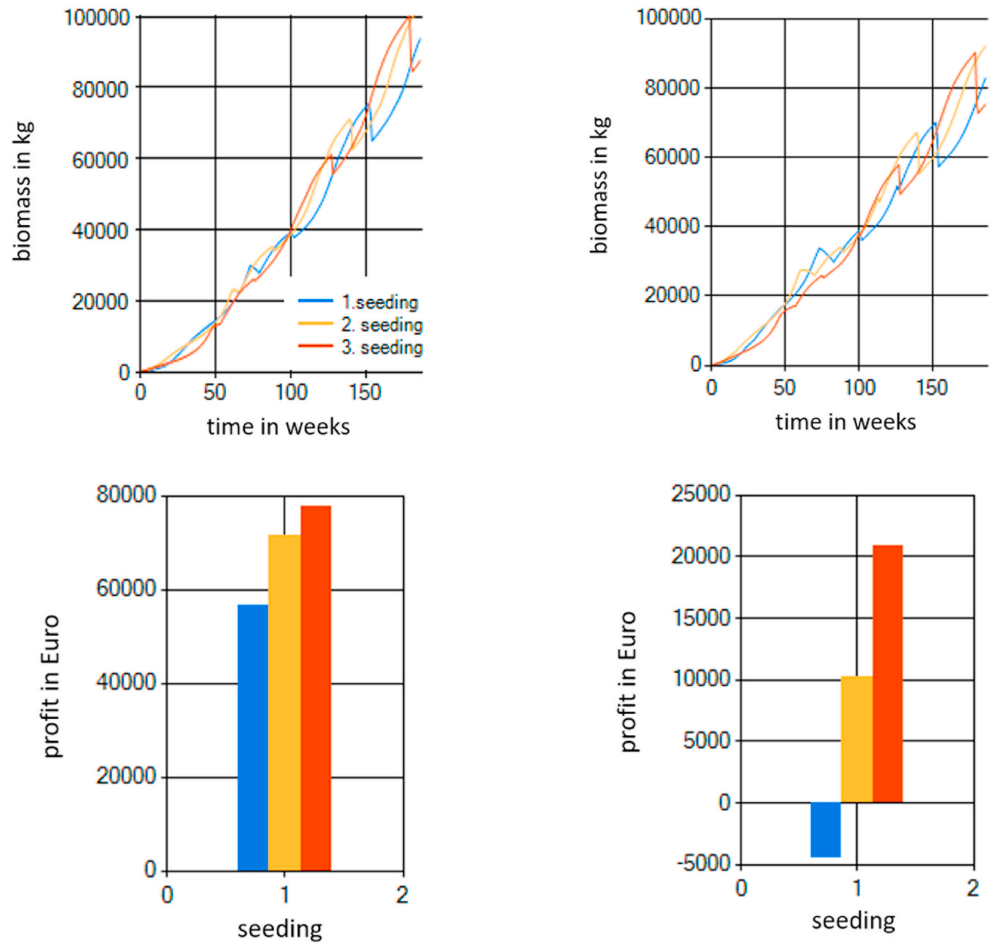

Fig. 8. Biomass (top) and profit (bottom) example for a model farm for E. seabass in regions R1 (left) and R9 (right) under RCP85. Colors denote the different seeding months (blue: March; orange: June; red: September).

register fewer biomass and profit losses (up to 20% depending on region and climate scenario) compared to inshore farms, thus pointing to potential benefits for expanding farming offshore as a potential climate adaptation measure. However, such an assessment should be interpreted with caution since it is sensitive to the severity one assigns to extreme events while it makes no assumptions for technological advancements in the sector which may mitigate the adverse effects of extreme weather events in the future.

In fact, the severity of extreme events, and particularly heatwaves, is among the most defining parameters for farm profitability as demonstrated by the relevant sensitivity analysis (Fig. 9). In this analysis, the default ClimeGreAq values for the various input variables were used to

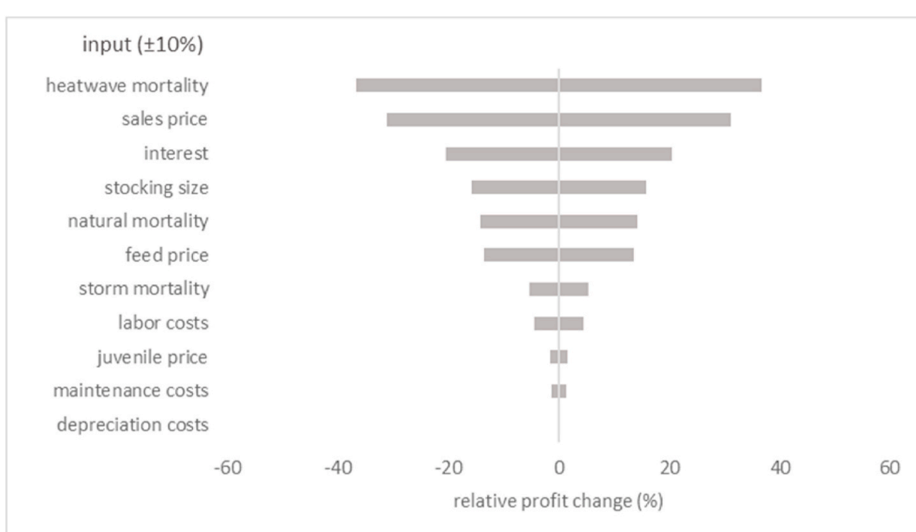

Fig. 9. Sensitivity analysis. Bars indicate the relative change in profit (%) for a farm subjected to a 10% change in the input variables.

calculate the profit for a farm, averaged over all regions and climate scenarios. Next, the relative changes in profit were calculated comparatively to that value for a 10% change in all input variables individually. The analysis showed that heatwave mortality had the highest impact on profitability followed by the sales price, interest and seeding size. Feeding and mortality (natural or due to storms) also had a substantial influence on profit while it was less affected by the various costs such as those of labor and maintenance.

Precisely due to the critical role of perceived extreme event severity for profitability, extreme event mortality has been left as an input parameter in the DSS, allowing users to further investigate climate change impacts on a scenario basis. For instance, a scenario-based approach to analyze the severity of extreme events across the dimensions considered here (regions, climate scenarios, stocking months, inshore/offshore locations) has been presented in Stavrakidis-Zachou et al. (2021). In that study, it was shown that scenarios of high and moderate severity for extreme events may lead to profit losses as high as 80% in the future, rendering farming a financially unviable activity for many regions. Moreover, even for scenarios of mild severity, profit losses could be substantial by 2050, in the order of 20–40% compared to present values. Therefore, although such an assessment may be prone to subjectivity, it may be still useful for detecting severe climate threats. In the present, the DSS achieves this by allowing investigation of extreme event scenarios according to the user's perception, thus increasing the overall flexibility of the tool.

Finally, an important factor for aquaculture is the seasonality of growth which is determined by the seasonal changes in temperature and the species-specific thermal preferences. Specifically, throughout the year environmental conditions fluctuate in a way that creates species-specific optimal time windows for growth followed by periods when growth declines or completely ceases. Consequently, considering these optimal growth periods is crucial when deciding the seeding strategy of a farm since this strategy determines the time required for fish to reach specific sizes. In fact, as shown in Table 3, specific seeding months may be preferable for growth, depending on the choice of species and climate scenario. Arguably, the choice of the harvest size has large economic implications in terms of both operational costs and sales prices. Therefore, the optimization of seeding is crucial, in order to achieve specific production goals for selected market sizes under different climate scenarios. ClimeGreAq provides a tool to investigate this via the optimization window and we show an example of suggested seeding for three market sizes under the same environmental scenario (Fig. 10).

The effect of the market size is considerable since it progresses from a balanced suggestion among the three seeding months for smaller sized E. seabass to a sole preference for a specific seeding month for larger sizes. In particular, while September seems to be the optimal seeding month for 400 g, March and June tend to be preferable for bigger sizes. However, this effect pertains to the region, time period and climate scenario investigated and therefore may differ considerably under different conditions.

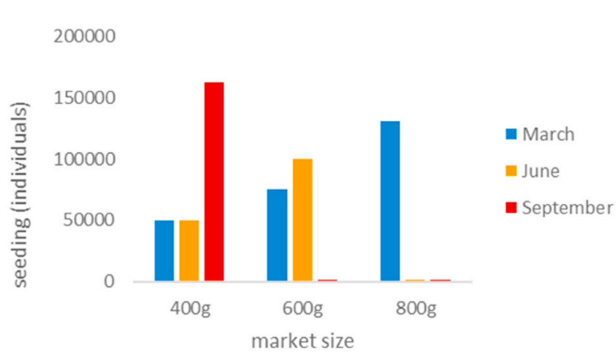

Fig. 10. Seeding optimization (number of individuals) for three market sizes (400, 600, 800 g) (parameters: region R1; E. seabass; 2045–2055; RCP8.5; inshore; 100 tons target production). Colors denote the different seeding months (blue: March; orange: June; red: September).

4. Discussion

Collaboration between scientists and stakeholders is crucial for the sustainable management of marine resources and the development of decision support (Österblom et al., 2020). In that regard, ClimeGreAq has been developed in collaboration with its intended users, aquaculture stakeholders. This process has not only ensured that crucial elements relevant for the users have been incorporated but also that the tool is user-friendly. While this is important for all types of decision support systems, it is particularly important for aquaculture because the complex interactions of the natural environment with the biology of the farmed fish as well as the rearing practices pose challenges in identifying key parameters for decision-making. In fact, such relevant parameters are often missing in many DSS (Mathisen et al., 2016). Unlike simpler systems, decision-making in aquaculture must integrate biological, economic, and environmental elements while at the same time accounting for farming practices and management drivers (Cobo et al., 2019). In this study, effort was made to incorporate several of these factors, including parameters that are linked to the environmental conditions during rearing such as the seeding month, the location (inshore of offshore) and the region, as well as population parameters (seeding size and mortality) and farm economics. While the inclusion of such parameters was not exhaustive, the co-creation approach ensured the incorporation of key parameters that are able to capture some of the complexities required for decision-making in aquaculture. Moreover, in line with stakeholder recommendations, an approach, not based on explicit modeling, was adopted to include additional climate drivers (extreme events) other than temperature. This contributed to increasing the versatility of the software and allows a more comprehensive evaluation of climate change effects. Finally, another advantage of the presented DSS is that its biological predictions are based on rigorous modeling that has been validated against production data (Stavrakidis-Zachou et al., 2019, 2021).

Being explicit about the capabilities as well as limitations of a DSS is fundamental to its correct use. Erroneous usage or misplaced expectations are counter-productive and may lead to loss of trust or reduced acceptance of such tools (Brauner et al., 2019). Therefore, it is important to acknowledge that any prediction of the future will carry inherent uncertainties. For ClimeGreAq, as indicated by the validation results, the uncertainty of the biological predictions is small and within the range reported for farmed finfish (Lupatsch et al., 2003; Navarro-Martín et al., 2009). However, ClimeGreAq faces the uncertainty typically encountered in climate modeling due to the selection of the global climate model, the IPCC scenario, and the downscaling method (Kay et al., 2008). For example, RCP4.5 was considered the most likely climate scenario when the development of ClimeGreAq started, yet, according to recent reports we are now heading closer to RCP8.5 (Teske, 2019). Therefore, the selection of the climate scenario alone is a major source of uncertainty that influences the predictions of the DSS. Similarly, predicting trends in economic variables remains highly speculative and, thus, the economic data input provided by the user adds to the overall uncertainty. However, these sources of uncertainty do not impede the functionality of the tool since its purpose is to provide a range of possible future outcomes and not to predict the future. In fact, comparing alternative future states and interpreting trends (which the DSS can facilitate) while understanding the limitations of predictions is fundamental for developing evidence-based, yet flexible, climate adaptation strategies. In that regard, it is also important that the DSS is presented and used as an aid to decision-making that does not, nor should, replace human decisions (Sturm et al., 2018).

Throughout the project and during the stakeholder meetings, care was taken to provide clarity about the limitations of the tool and ensure its appropriate application. With respect to the limitations, environmental drivers associated with climate change such as acidification, salinity, HABs, and changes in water circulation patterns were not considered for the biological simulations while extreme weather events were included but their underlying mechanisms not explicitly modeled. Therefore, ClimeGreAq is not a suitable tool for studying the effects of these drivers directly nor the interactions between them. However, users could potentially explore their effects on farm economics indirectly by incorporating them as changes in mortality or associated costs. Moreover, the spatial analysis of ClimeGreAq is limited by the resolution of the available climate models. Consequently, while it is appropriate for detecting large scale trends, its application to fine spatial scales may be compromised. Another limitation is that the tool relies on precomputed biological simulations. Although significant effort was made to cover a large number of scenarios, these simulations are finite and thus set a limit to the range of scenarios that can be investigated.

Finally, the DSS has been developed as an aid for making strategic decisions but not as an operational tool to be used for the day-to-day operations of a farm. While the software contains elements that could be used for this purpose, it has not been validated and calibrated to accommodate such needs and this is communicated in the disclaimers found in the DSS. An example of this is the daily feeding operations of a farm. Although ClimeGreAq simulates the feed consumption for the fish population it should not be used as a reliable tool for calculating the daily feeding scheme for a farm since important variables relating to feeding such as the feed composition or the meal distribution over the day have not been explicitly modeled. In such cases, dedicated tools should be used instead (Cobo et al., 2019). On the other hand, ClimeGreAq considers climatic effects at a wide spatiotemporal scale while also accounting for husbandry and economic indicators, and thus, it may be used to investigate alternative what-if scenarios for the future and support strategic decisions related to climate change adaptation.

As explained above, ClimeGreAq can capture changes in biological performance at the individual and population levels, suggest optimal seeding schemes, and translate biological input into changes in profitability under different climate scenarios and time horizons. Furthermore, based on the user's perception of how relevant farm economic parameters may develop in the future under the various IPCC scenarios, a whole new range of scenarios can be tested and visualized by adjusting the corresponding farm economic variables. This information can then be used by aquaculture stakeholders to serve their specific decision-making needs. For a producer, this type of information could contribute to decisions that make better use of the projected environmental changes in order to grow fish faster and at a lower cost. These decisions may relate to the seeding scheme (timing and size), the selection of favorable sites for expansion or translocation of the farming activity offshore, and the choice of target species and profitable market sizes. On the other hand, the administrative authorities could use the DSS as a tool to investigate shifts in production capacity at a regional scale in order to designate new Zones of Organized Development of Aquaculture (Z.O.D.A) in a way that promotes the sustainable expansion of fish farming in Greece under climate change. Finally, the supporting information on the related risks and potential adaptation measures could further contribute to shifts in farming practices or the development of national climate adaptation strategies for aquaculture.

Although ClimeGreAq has been delivered in its final form, future needs may necessitate changes in order for the tool to remain relevant in the long term. Lines of future research could incorporate the effects of additional climate drivers such as acidification, HABs and oxygen limitations. Other updates could entail new biological simulations based on updated climate models both in terms of reliability and spatiotemporal resolution. Furthermore, as already mentioned, ClimeGreAq in its present form relies on precomputed simulations and although this does not limit its functionality, a modified version could potentially include the model itself, thus allowing the simulation of additional scenarios. Moreover, the tool could be updated to include additional aquaculture species and new regions if relevant data becomes available. Finally, from an economic perspective, ClimeGreAq could provide a basis for a tool to assess how climate change and appropriate adaptation strategies might impact the gross value added of Greek aquaculture as a whole.

5. Conclusion

In conclusion, the software-based DSS presented here aims to support decision-making in Greek aquaculture under climate change by simulating and visualizing climate impacts on biological and farm economic indicators. Based on a bio-economic approach and developed in collaboration with stakeholders, it incorporates key variables that are able to capture some of the complexities of the industry, which renders it suitable for supporting strategic decisions in aquaculture. To our knowledge, this is the first case of an interactive tool developed for marine aquaculture that specifically tackles climate change challenges. Thus, it has the capacity to contribute greatly to the adaptation of marine aquaculture to climate change and thus the sustainable growth of the sector in the future.

Software and data availability

The DSS was developed in the context of the EU project Climefish (https://climefish.eu/). Regarding its technical implementation, it is available for Microsoft Windows. Open source software was used for the various components while the programming language was C#. Regarding the local database, where all information is stored including the biological pre-computed simulations and supporting farm economic data and parameters, it uses a free version of the MySQL Community Server release (8.0.2) which was deemed sufficient to support the DSS functions. An executable of the software can be freely accessed via the ClimeFish community at zenodo (https://zenodo.org/record/3627546#.XonXUXJS82w) or in the ClimeFish toolbox (http://136.144.228.39:8080/climefish) along with supporting information such as instructions and a user manual. To operate the DSS, prior installation of the MySQL (https://zenodo.org/record/3627369#.XonXaHJS82w) is required, which can also be performed with open source software (XAMPP, 2020).

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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