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Title: Economic optimisation in seabream (*Sparus aurata*) aquaculture production using a particle swarm optimisation algorithm

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ABSTRACT

The purpose of this study is the economic optimisation of seabream farming through the determination of the production strategies that maximise the present operating profits of the cultivation process. The methodology applied is a particle swarm optimisation algorithm based on a bioeconomic model that simulates the process of seabream fattening. The biological submodel consists of three interrelated processes, stocking, growth, and mortality, and the economic submodel considers costs and revenues related to the production process. Application of the algorithm to seabream farming in Spain reveals that the activity is profitable and shows competitive differences associated with location. Additionally, the applications of the particle swarm optimisation algorithm could be of interest for the management of other important species, such as salmon (*Salmo salar*), catfish (*Ictalurus punctatus*) or tilapia (*Oreochromis niloticus*).

Keywords Bioeconomics · Economic optimisation · Operational research · Particle swarm optimisation · Seabream · *Sparus aurata*

Introduction

The gilthead seabream (*Sparus aurata*) production in the Mediterranean Sea has experienced a rapid growth over the last 20 years. Nowadays, seabream cultivation represents the most important production of fish in this geographical area. However, the uncontrolled increase in the supply has caused a loss of competitiveness at many companies (Llorente and Luna 2012). In the Mediterranean area, consumers mainly demand fresh and unprocessed seabream, which makes difficult to differentiate the product. In this context, the main driver in the purchase decision is the price. During situations of oversupply prices fall to levels that for some farmers are below the cost of production, causing the bankruptcy of many companies.

These economic problems have shown that biological viability and the necessary technology to implement commercial scale production are not enough to develop an aquaculture production economically sustainable. The development of more efficient and productive management systems has been one of the main solutions of the aquaculture industry to solve this problem. These systems have been developed through the use of Operational Research (OR) methods (Hernández et al. 2007). The OR models applied in aquaculture have been based on accumulated experience in fishing and other primary sector activities, such as agriculture or forestry, to increase the efficiency and profitability of fish farming on an industrial scale (Bjørndal et al. 2004).

By modelling the complex interactions between economic and biological systems, it is possible to make the most efficient decisions about aspects such as the diet composition, feeding rates, and harvesting time (León et al. 2001). Many applications of bioeconomic models to aquaculture management have been described in the literature. Examples for particular species can be found in Bjørndal (1990), Cacho et al. (1990), Leung and Shang (1989), Rizzo and Spagnolo (1996), Sparre (1976), and Gasca-Leyva et al. (2002), for salmon

(*Salmo salar*), catfish (*Ictalurus punctatus*), freshwater prawns, European seabass (*Dicentrarchus labrax*), trout (*Oncorhynchus mykiss*), and gilthead seabream, respectively. These models are integrated via a biological sub-model of fish growth and an economic sub-model that links the process of production to markets through the costs of inputs, the prices of outputs and resource constraints.

There are examples in the literature of OR models that optimise management strategies and profitability considering biological relationships in a more general context. Bjørndal (1988) analysed the optimal harvest strategy for aquaculture based on a static optimisation problem under different conditions related to the sale price and the main costs of production, including feed. Arnason (1992) extended his analysis to an explicitly dynamic framework involving both feeding schedules and the harvesting time. Other results in the same framework were obtained including the possibility of a previous harvest (Heaps 1993), a price dependent function related to the weight of the fish (Mistiaen and Strand 1999) or the influence of factors such as ration size and water temperature (Hernández et al. 2007). A review of OR techniques applied to fisheries and aquaculture in the past forty years is available in Bjørndal et al. (2004).

Although these studies have contributed significantly to the economic optimisation of production strategy, the complex interactions of technical, biological, environmental, and economic aspects in fish farming limit the application of classical optimisation methods. In recent decades, there have been several optimisation techniques applied to OR in aquaculture, such as dynamic optimisation (Rauch et al. 1975; Karp et al. 1986; Bjørndal 1988; Arnason 1992; Mistiaen and Strand 1999), dynamic programming (McNown and Seireg 1983; Leung 1986; Leung and Shang 1989), linear programming (Gates and Mueller 1975; Forsberg 1996; Yu and Leung 2005), and nonlinear programming (Rizzo and Spagnolo 1996). A useful method when the optimisation problem is nonlinear, complex, and multidimensional is

Particle Swarm Optimisation (PSO). PSO is a metaheuristic technique based on evolution of populations for problem solving that was originally developed by Eberhart and Kennedy (1995).

The purpose of the present study is the economic optimisation of seabream aquaculture production through the determination of the production strategies that maximise the present profits of the farming process. The methodology used is a PSO algorithm based on a bioeconomic model for the simulation of seabream fattening in floating cages. The algorithm is applied to the seabream production in Spain. This country is one of the main producers of this species. However, at present, the Spanish seabream industry has profitability problems due to increased market competitiveness. The use of PSO algorithms to optimise seabream aquaculture production in economic terms helps to improve knowledge on aquaculture management.

Materials and methods

Bioeconomic model for seabream aquaculture

The present study applies the bioeconomic model described in a previous research done by Llorente and Luna (2013), introducing the PSO methodology to research on aquaculture. The purpose of the bioeconomic analysis is to find a harvesting time that maximises the present operating profits in a given time horizon (Asche and Bjørndal 2011). The bioeconomic model used in this study is integrated via a biological sub-model of the process of farming in sea cages, while also being interrelated with an economic sub-model that quantifies the economic implications of any change in the farming and market parameters. For the period analysed, it is necessary to determine the number of batches and, for each batch, the times, weights, and densities of stocking and harvesting. The use of scientific knowledge accumulated in the literature avoids the need for developing complex and costly experiments to determine the model equations.

The bioeconomic model for seabream used in this study includes some changes with respect to that developed by Hernández et al. (2003). The model takes into account the rotation problem proposed by Bjørndal (1988). When fish are actually harvested, space is made available for new fish. This is important, as the available space in fish farms is limited. Producers can increase the value of biomass by replacing slower growing old fish with faster growing young fish. Thus, the problem is reduced to finding the optimal rotation time for a batch of fish, i.e., the time for harvesting one batch and stocking the next.

The breeding process over time is described by the fish weight (w), number of fish (N), time (t), production costs (C), and revenues (R). For each batch, the decision variables are the stocking time (t_0), the weight of fingerlings stocked (w_0), and the weight of fish harvested (w_h). Because the water temperature and feeding rates are considered deterministic, the time of stocking and the weight of fingerlings define a single trajectory of growth until reaching the selected harvest weight. Temperature, together with the weight of the fingerlings released, determines the growth and mortality of the fish. Finally, the obtained harvest weight (body mass at harvest) determines the time of harvest. The model includes three essential factors that influence fish growth: fish weight, water temperature, and feed quantity, defined as the feed ration given to fish. To isolate it from the influence of other factors, the model is formulated according to several assumptions explained in detail in Llorente and Luna (2013). The nomenclature used in the bioeconomic model is available in Table 1.

The biological model simulates the breeding process: the fingerlings are stocked, and the fish are fed depending on their weight and the water temperature. The biological model follows the principles of fish physiology (Brett and Groves 1979), which were first considered in modelling the growth of salmonids by Stauffer (1973). It consists of three interrelated processes: stocking, fattening, and mortality. The number of fingerlings stocked is calculated to obtain the maximum biomass density (D_{max}) at harvesting time (Equation 1 in

Table 2). Fish growth is obtained from feeding, which is a function of the water temperature and the average weight of the fish (Brett and Groves 1979). Growth is simulated using the expression in Equation 2. As in the work addressing the optimal management of seabass aquaculture developed by Rizzo and Spagnolo (1996), information on the specific growth rate is obtained from the average values in the feeding tables provided by feed suppliers and often used by fish farmers. These tables, depending on fish weight and water temperature, indicate the optimal feed ration and the resulting growth rate. The average weight of the individuals at time t (w_t) and at harvesting time (w_h) is then given by Equation 3 and Equation 4 respectively. The suffix k is a variable representing each time interval between the times of stocking (t_0) and harvesting (t_h). The survival of individuals depends on the biomass density, the fish weight, and the environmental conditions. In this study the biomass density is a fixed value, the mortality in a given period is specified as in Equation 5 and survival at the beginning of t can be expressed as in Equation 6.

The economic model is a maximisation problem based on an objective function that is optimised considering the income and the production costs and can be expressed as in Equation 7. The stocking time of the first batch is defined as *time zero*. To calculate the present monetary value, each cash flow value is multiplied by the corresponding discount factor DF (t), calculated as in Equation 8. The parameter i is the annual discount rate or cost of capital, which is used as the rate of return. Revenues for a batch are expressed in the Equation 9. The parameter $q_h(t_h)$ is a function that returns a factor to include the effect of seasonality of the sale price. The number of fish harvested in a batch is expressed in Equation 10. The total cost of each batch is given by the Equation 11, in which C_r is the cost of fingerlings, and C_f is the cost of feed. The cost of fingerlings for a batch b is expressed in Equation 12, in which $q_s(t_0)$ is the function that returns a factor to include the effect of seasonal variation on fingerling price. The feed cost of a batch can be expressed as in

Equation 13. It is assumed that the fish are fed at least once a day. The parameter F is the function that returns the feeding rates, which are expressed as a percentage of fish weight. A discount factor is also included because it is assumed that the feed is purchased when it is provided to the fish. Therefore, the cost of food in each time interval is discounted to $k = 0$, and $DF(k_b)$ is the corresponding discount factor.

PSO algorithm for aquaculture production

PSO algorithms are population based metaheuristic techniques inspired by the social behaviour during flight observed in flocks of birds or the movements occurring during fish schooling. Optimisation using PSO algorithms was initially developed to simulate social behaviour. These algorithms were subsequently investigated in depth by many authors and successfully applied in many research fields (Poli et al. 2007). These methodologies belong to a group of optimisation techniques in the field of Artificial Intelligence known as Swarm Intelligence (SI) (Bonabeau et al. 1999). SI techniques are less well known than other metaheuristic techniques based on populations, such as Genetic Algorithms (GA). However, some experimental studies show the best effectiveness of SI in addressing combinatorial optimisation problems (Mouser and Dunn 2005; Uysal and Bulkan 2008).

PSO algorithms represent an iterative and stochastic process that always works with a group of particles placed in a search space of some problem. The particles move in successive iterations through cooperation and competition between individuals in the population. Each particle evaluates the objective function in its current position and therefore represents a possible solution to the problem. To obtain a new position in the search space, a particle moves from one position to another after adding the vector v_i to the vector x_i:

$$x_i \leftarrow x_i + v_i \tag{14}$$

The x_i vector contains the current state of the particle in the search space and the velocity vector (v_i) indicates the direction and distance of displacement of the particle. Each particle adjusts its speed and position according to the following expressions

$$v_i^{t+1} = v_i^t + \varphi_1 r_1^t (pb_i^t - x_i^t) + \varphi_2 r_2^t (pg_i^t - x_i^t) \tag{15}$$

$$x_i^{t+1} \leftarrow x_i^t + v_i^{t+1} \tag{16}$$

where φ_1 and φ_2 are parameters for weighting the importance of the personal experience of the particle and the global experience of the neighbourhood, respectively. Parameters r_1 (t) and r_2 (t) are two random numbers with uniform distribution [0,1] included to enrich the searching space. Parameters pb_i and pg_i are position vectors that represent the best position that each particle and their sets of neighbouring particles have found to date in the search space, respectively. The update of the velocities given in the Equation 15 involves three components. The *inertial* component is modelled by the factor v_i^t and remembers the previous address of the particle. The *cognitive* component is modelled by the factor $\varphi_1 r_1^t (pb_i^t - x_i^t)$ and directs the particle towards the best solution in the past. The *social* component is modelled by the factor $\varphi_2 r_2^t (pg_i^t - x_i^t)$ and directs the particle towards the best position found by its neighbouring particles.

Many strategic and operational decisions in fish farming can be optimised by mathematical modelling, e.g., stocking strategy, feeding rate, harvesting time, and harvest weight. However, the complexity of the aquaculture production process makes difficult to find the universal optimal solution. Metaheuristic methods like the PSO are good at exploring the solution surface approximating global solutions in reasonable computation times (Osman and Laporte 1996; Blum and Roli 2003).

This study is performed during the fattening of fingerlings until reaching commercial size. Each particle of the population in the search space represents a production strategy. Each position of the particle evaluates the objective function and determines a profit, considered as the sum of the profits of all batches. These processes must be performed entirely within the established time horizon. If the harvest time of a batch corresponds to a later date, the profit of this process is void. According to the general scheme of all PSO algorithms, each particle i has an associated position vector x_i that represents the corresponding production strategy. The structure of each of these vectors is described for each of the t iterations of the algorithm as follows:

$$x_i^t = (re_{i,1}^t, pd_{i,1}^t, pa_{i,1}^t; re_{i,2}^t, pd_{i,2}^t, pa_{i,2}^t; re_{i,3}^t, pd_{i,3}^t, pa_{i,3}^t; \ldots; re_{i,n}^t, pd_{i,n}^t, pa_{i,n}^t) \qquad (17)$$

where n is the maximum number of batches obtained in the time horizon considered. For b batches, $re_{i,b}^t$ represents the number of days with respect to the previous harvest process, $pd_{i,b}^t$ represents the desired harvest weight of the fish, $pa_{i,b}^t$ represents the fingerling weight.

The objective function is obtained by substituting equations (8) to (13) in (7), so the operating profits can be expressed in terms of seven variables. The state of production at any time t is described by the state variables w_t, N_t, m_t, and T_t. Fish farmers, in this case the algorithm, must decide the values of the decision variables (t_0, w_0, and w_h) for each batch.

Models for simulation and optimisation were implemented into computer with a specific software developed *ad hoc* for this study, using the Integrated Development Environment (IDE) Netbeans.6.7.1 with Java programming language and MySQL database connectivity.

Simulation optimisation of seabream production in Spain

The PSO algorithm was applied to the production of gilthead seabream in floating cages for two locations, the Canary Islands and the Mediterranean (Spanish east coast). It is necessary to differentiate between the two main production areas due to the different environmental conditions under which cultivation is developed. The optimal production strategy was obtained for both locations for a hypothetical fish farm under the same cultivation conditions, with the exception of water temperature. The parameters that define the characteristics of the seabream farm proposed and the settings for the control variables are shown in Table 3.

The price of fingerlings was obtained for the major hatcheries in Spain. The seasonality of fingerling price was not considered. The average selling prices corresponded to the monthly average values observed for the seabream in Mercamadrid in 2009. The seasonality of the average selling price was calculated as the monthly variation of the average annual price. Information on water temperatures comes from the weather buoy network of the Spanish Port Authority (Table 4). These data, with 24 daily references, cover a period ranging from the onset of activity of each buoy to March 1st, 2009. The types of feed that are used to calculate the average values in the feeding tables used in this analysis come from the following companies: PROaqua (Mistral 21), Skretting (Basic and Power), DIBAQ (Ecoprime and Ecomar), and Acuibream (5, 6, 7, and 8). Full details about the data used are available in the Appendix B in the paper developed by Llorente and Luna (2013).

The algorithm parameters are shown in Table 5. These values are a particular problem due to their influence on the behaviour of the PSO algorithm. The usual criterion is to set the values according to the dimension of the search space and the perceived difficulty of the problem (Poli et al. 2007).

Results

The simulation results showed that under the production conditions simulated, the optimal production strategy for seabream farming in the Canary Islands (Figure 1; Table 6) includes the development of five batches over the time horizon of five years. In the first batch, fingerlings with a weight of five grams are stocked in early January. The cultivation process is developed over 535 days. At harvesting time, the fish weight is 512g, and the sale price is 13.1% above average price. The next batch, using fingerlings of three grams, is stocked the same day as the previous harvest to achieve a harvest weight of 304g in 374 days. The harvesting of this batch is also performed in June, which is the month of the year in which the sales price is highest. The third batch is initiated three days after the second harvest. Fingerlings of eight grams are stocked, and the fish reach a harvest weight of 300g after 298 days of cultivation. At harvest time, the sales price is 7.8% higher than the average price. The next batch begins the same day. Fingerlings with a weight of seven grams are stocked to achieve a harvest weight of 301g in 310 days. The harvesting time is in March, when the corresponding price premium is 5.3% above average price. The last batch of the time horizon analysed begins two days later. Fingerlings of 10 g are stocked, and the fish reach a harvest weight of 300g after 301 days of cultivation. The present value of the operating profits obtained using this strategy in the period of analysis is 243 € per m^3.

In the case of seabream production in the Mediterranean, the optimal production strategy (Figure 1; Table 6) involves the development of four batches in the time horizon considered. In the first batch, fingerlings of eight grams are stocked to reach a harvest weight of 300g in 519 days. As in the Canary Islands, the harvesting of this batch is performed in June, in which the sales price is the highest, at 13% higher than average. The second batch involves the release of fingerlings of 10 g on the same day as the previous harvest to reach a harvest weight of 302g in 389 days. The third batch is initiated at the end of June. Fingerlings of seven grams are stocked, and the fish reach a harvest weight of 301 g after 398 days of cultivation. The last batch of the time horizon analysed begins on the same day as the third batch is harvested. Fingerlings with a weight of six grams are stocked to achieve a harvest weight of 300g in 397 days. The present value of the operating profits obtained with this strategy in the period of analysis is 187 € per m^3.

For the example simulated, the operating profits differ between the Canary Islands and the Mediterranean despite working under the same production parameters and during the same period of time. The water temperature associated with the locations is the reason for which the productivity and the economic results of the two sites are different. The water temperature generates a cyclical behaviour in the seabream production that is much stronger in the Mediterranean than in the Canary Islands, where the production process is more continuous during all the year.

In the Canary Islands, the average annual water temperature is 21.1ºC, with a maximum of 23.9ºC in October and a minimum of 19.50ºC in March and April, whereas in the Mediterranean, the average water temperature is 18.5ºC, with a maximum of 25°C in August and a minimum of 13.50ºC in February. Thus, there is less variability of the water temperature in the Canary Islands than in the Mediterranean, which exhibit standard deviations of 1.5 and 4.05, respectively. The lower variability of water temperature in the Canary Islands prevents the occurrence of periods of the year in which the metabolic activity of the fish decreases and fish growth is low or zero, as found in other locations.

During the summer months, the water temperature is similar in the two locations, and therefore, the food conversion rate is also similar. However, the water temperature is higher during the rest of the year in the Canary Islands, with differences in excess of six degrees being observed, such as in January. As a result of the different temperatures, the feed conversion rates associated with seabream production are different between the Canary Islands and the Mediterranean (Figure 2). The average feed conversion rates, expressed as the ratio of the provided food and the harvested biomass (feed supplied/weight gain), are 1.69 and 1.82, respectively.

Discussion

The increased competition in the seabream market resulted in a reduction in the operative margins that has affected the profitability of companies. In recent years, many companies have not achieved a positive economic return. However, the economic problems of seabream companies in Spain are not derived from a lack of profitability of this activity. The optimal production strategies obtained in the simulation for the two main cultivation areas in Spain, the Canary Islands and the Mediterranean, are profitable. The lack of competitiveness of many companies in the seabream industry does not come from biological or technical aspects, but arises from the difficulty of the economic and management decision-making process. Results presented in this paper suggest that the application of more efficient and productive management techniques like the applied in the present study would help to maximise the economic performance of the activity and recover lost competitiveness.

The application of the PSO algorithm also allows to identify the production strategies that maximise operating profits. Seabream markets are very seasonal due to the influence of the environmental conditions in the cultivation process (Luna 2002). Previous studies showed a positive effect of an increase in the average water temperature on the harvesting size (Hernández et al. 2007). Traditionally, to produce a batch in the most efficient way (requiring less time and less feed) fish farmers usually feed fish under higher temperatures due to the better conversion rates, avoiding feeding in periods of cooler waters, which are associated with lower conversions rates. This situation generates a high seasonality of supply and output prices. However, given the assumptions and parameters simulated in this example, the optimal strategies that maximise the operating profits in both locations require feeding the fish during the period of higher supply and lower market prices, and harvest the seabream when the other producers reduce their supply and as a result, market prices are higher (Figure 1).

The results obtained are perfectly valid short run results, as the producers are price takers. However, in the long run, these profits from going against common practice of the industry and taking a competitive advantage from the seasonality in production will be reduced. As more and more producers follow the optimal strategy obtained in this study, the benefits derived from it will be lower. If the industry increases the supply of seabream in summer, prices will be reduced until a critical point where the increase in revenues derived from harvest during summer will be proportionately lower than the increase in feed costs during winter. The analysis of how the industry behaviour will affect to the optimal production strategy of a company in the long run would require the incorporation of the industry long-run dynamics directly into the model and this issue has not been addressed yet. However, what it can be expected from this analysis is that if every producer follows the strategy obtained in this study, the price seasonality would change and the optimal strategy would have to be adapted to the new situation.

In this study the quantity of production is limited by the maximum biomass density. Therefore, considering that the production capacity of the cage is $100m^3$ and the maximum biomass density is $20kg/m^3$, the maximum amount of seabream that can be produced in each batch is 2,000kg. The maximum quantity of production per batch can be achieved with different harvest weights and thus with different number of individuals harvested. Several previous studies concluded that those batches that produce larger fish reach higher operating profits due to its higher value in the market (Gasca-Leyva et al. 2003; Hernández et al. 2007). The results of the current study are consistent with those obtained in these previous works. The batch that produced the larger size (Batch 1 in the Canary Islands) got the greater operating profit, compared to the other batches. However, the rotation problem which is a main issue in the optimal management of aquaculture and forestry was not analysed in these previous studies as noted in the conclusions of the study by Hernández et al. (2007). The consideration in this work of a multi-batch production has allowed analysing the effect of productivity on the operating profitability. Considering the entire production period instead of just one batch, the best economic results were obtained by producing the maximum number of batches in the period analysed, not by producing larger sizes. Consequently, strategies that maximise the present value of the operating profits were those that achieved a higher productivity in the period analysed.

The comparison of the two locations shows the existence of competitive differences arising from their environmental conditions. In a context where the optimal strategy that maximise profits requires feeding the seabream during the cold water periods, firms with higher average water temperature during the winter months are more efficient due to the better feed conversion rate that they achieve. The facility located in the Canary Islands exhibits better economic performance compared to that located in the Mediterranean due to the higher productivity achieved. These competitive advantages influence the production strategies that optimise the operational economic performance of seabream companies. These results are consistent with previous works (Gasca-Leyva 1999; Hernández et al. 2003; Hernández et al. 2007; Llorente and Luna 2013)

Some limitations of the study should be noted. Currently, the algorithm optimises only the economic performance of a cage or production unit. The difficulty of the optimisation problem increases exponentially when more than one cage is introduced. Furthermore, it is assumed that at the beginning of each batch, the cage is empty and that during the cultivation process, there is no possibility of performing partial harvests. All of these issues should be addressed in further research.

Despite the limitations considered above, the study also suggests other research directions. Firstly, it is necessary to incorporate the industry dynamics into the model to determine its influence on the strategies of production in the long term. Secondly, it would be useful to analyse the optimal geographical location of an aquaculture farm taking into account the role of the environmental conditions and the distance to the markets as sources of competitive advantages. This will provide evidence if or not these two factors have a positive or negative influence in the economic result in the different seabream production areas around the Mediterranean Sea. Finally, the algorithm used could be of interest for the economic optimisation in the production of other important farmed species such as salmon, catfish, or tilapia, and for other sectors related to aquaculture, such as insurance or finance.

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Figure legends

Figure 1 Evolution of the seabream weight (w) and the seasonality of its price (q_h) in the Canary Islands and on the Spanish Mediterranean coast along the five years period simulated

Figure 2 Evolution of the feed conversion rate during the production of seabream in the Canary Islands and on the Spanish Mediterranean coast along the five years period simulated

Tables

TABLE 1 Nomenclature used in the bioeconomic model (Llorente and Luna 2013)

B	Total number of batches	$p_s(w_{0,b})$	Fingerling price at stocking time in batch b
b	Batch	$q_h(t_{h,b})$	Seasonality of sales price at harvesting time in batch b
C_b	Cost of production at batch b	$q_s(t_{0,b})$	Seasonality of fingerling price at stocking time in batch b
$C_{f,b}$	Feeding cost at batch b	R_b	Revenues at batch b
$C_{r,b}$	Fingerling cost at batch b	$SGR\ (T_t, w_t)$ $SGR\ (T_k, w_k)$	Specific growth rate at time t and k respectively
D_{max}	Maximum biomass density	$s_{h,b}$	Survival rate at harvesting time in batch b
$DF(t)$	Discount factor	s_t	Survival rate at time t
$DF(t_{h,b})$	Discount factor from harvesting time at batch b to	T_t , T_k	Water temperature at time t and k respectively

	time zero		
$DF(t_{0,b})$	Discount factor from stocking time at batch b to time zero	$T_{k,b}$	Water temperature at time t in batch b
$DF(k_b)$	Discount factor from time k to k = 0 at batch b	t	Interval of time considered
$F\left(T_{k,b}, w_{k,b}\right)$	Feeding rate at time k in batch b	$t_{h,b}$	Harvesting time at batch b
i	Rate of return	$t_{0,b}$	Stocking time at batch b
m_t, m_k	Mortality rate at time t and k respectively	w_h	Harvesting weight
$N_{s,b}$	Number of fingerlings released at batch b	$w_{h,b}$	Harvesting weight at batch b
$N_{h,b}$	Number of fish harvested at batch b	w_t, w_k	Fish weight at time t and k respectively
$N_{k,b}$	Number of fish at time k in batch b	$w_{k,b}$	Fish weight at time k in batch b
$p_f\left(w_{k,b}\right)$	Feed price at time k in batch b	w_0	Fingerling weight at stocking time
$p_h\left(w_{h,b}\right)$	Sales price at harvesting time in batch b	$w_{0,b}$	Fingerling weight at stocking time in batch b

TABLE 2 Bioeconomic model for seabream production (Llorente and Luna 2013)

Biological submodel		Economic submodel	
(1)	$N_{s,b}=\dfrac{D_{max}}{w_{h,b}\,s_{h,b}}$	(7)	$Max\ \pi = \sum_{b=1}^{B}(R_b\,DF(t_{h,b}) - C_b\,DF(t_{0,b}))$
(2)	$w_{t+1}= w_t\,(1+SGR(T_t\,,\,w_t))$	(8)	$DF(t) = (1+i)^{-t/360}$
(3)	$w_t= w_0\prod_{k=0}^{t-1}(1+SGR(T_k\,,\,w_k))$	(9)	$R_b= N_{h,b}\,w_{h,b}\;p_h(w_{h,b})\,q_h(t_{h,b})$
(4)	$w_h= w_0\prod_{k=0}^{h-1}(1+SGR(T_k\,,\,w_k))$	(10)	$N_{h,b}= N_{s,b}\,s_{h,b}$
(5)	$m_t= MOR(T_t\,,\,w_t)$	(11)	$C_b= C_{r,b} + C_{f,b}$
(6)	$s_t=1-\prod_{k=0}^{t-1}m_k$	(12)	$C_{r,b}= N_{s,b}\;p_s(w_{0,b})\,q_s(t_{0,b})$
		(13)	$C_{f,b}= \sum_{k=0}^{h-1}N_{k,b}\,w_{k,b}\,F(T_{k,b}\,,w_{k,b})\,p_f(w_{k,b})\,DF(k_b)$

TABLE 3 Simulation parameters. Characteristics of the seabream farm and settings for the control variables

Parameter	Value
Maximum biomass density	20kg/m^3
Cage production capacity	100m^3
Maximum number of days between harvesting and stocking	60 days
Feasible harvest sizes	[300 , 600] g
Available juvenile weights	[3 , 10] g
Time horizon	5 years from January 1st, 2009
Annual interest rate	5%

TABLE 4 Water temperatures (°C)

Month	Canary Islands	Mediterranean coast
January	20.5	14.1
February	19.7	13.5
March	19.5	13.8
April	19.5	14.9
May	19.7	17.8
June	20.0	20.3
July	21.0	23.0
August	22.0	25.4
September	23.3	24.3
October	23.9	21.1
November	22.7	18.7
December	21.5	16.2

TABLE 5 Value of the control parameters of PSO algorithm

Parameter	Value
Number of particles	80
Neighbourhood size (particles)	20
Inertia weight (w)	1.0
Weight of the cognitive component (φ_1)	0.4
Weight of the social component (φ_2)	1.0
Stopping criterion (number of consecutive iterations without improvement)	15

TABLE 6 Optimal strategies for the production of seabream in the Canary Islands and on the Spanish Mediterranean coast

Location	Variable	Batch 1	Batch 2	Batch 3	Batch 4	Batch 5
Canary Islands	Stock. Date	1/1/2009	20/6/2010	2/7/2011	25/4/2012	3/3/2013
	Harv. Date	20/6/2010	29/6/2011	25/4/2012	01/3/2013	29/12/2013
	Batch (days)	535	374	298	310	301
	Stock.Weight (g)	5	3	8	7	10
	Fingerlings	4,139	6,866	6,885	6,891	6,916
	Harv. Weight (g)	512	304	300	301	300
	Individuals	3,909	6,575	6,661	6,638	6,664
	Profits (€)	6,277	5,452	4,806	4,725	3,041
Mediterranean	Stock. Date	1/1/2009	4/6/2010	28/6/2011	30/7/2012	-
	Harv. Date	4/6/2010	28/6/2011	30/7/2012	31/8/2013	-
	Batch (days)	519	389	398	397	-
	Stock.Weight (g)	8	10	7	6	-
	Fingerlings	7,057	6,881	6,938	6,961	-
	Harv. Weight (g)	300	302	301	300	-
	Individuals	6,650	6,626	6,645	6,663	-
	Profits (€)	4,725	4,791	4,724	4,464	-

Figure 1

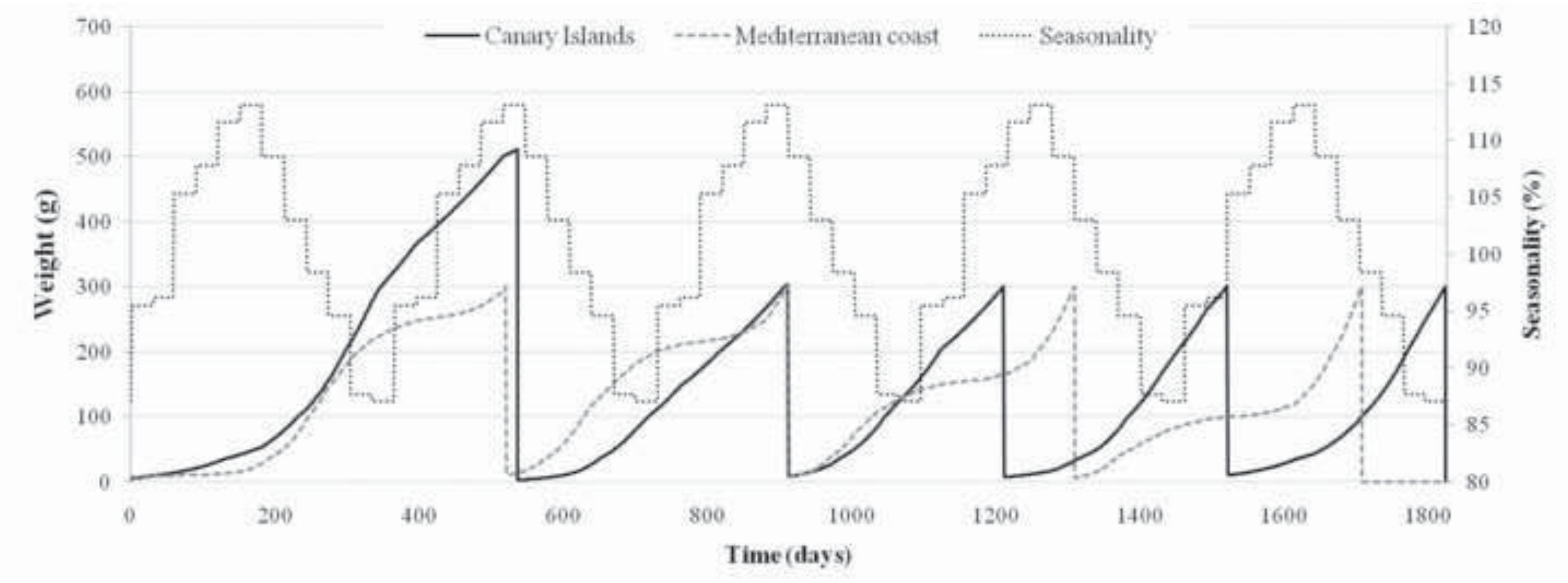
Canary Islands
Mediterranean coast
Seasonality
Weight (g)
0
100
200
300
400
500
600
700
Seasonality (%)
80
85
90
95
100
105
110
115
120
Time (days)
0
200
400
600
800
1000
1200
1400
1600
1800

Figure 2
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