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Abstract

The effects of random environmental impacts on optimal exploitation of a fish population are investigated using both optimization and simulation, based on a discrete-time age-structured bioeconomic model. The optimization problem is solved as a non-linear programming problem in GAMS. First, a basic model structure and 6 different scenarios, dealing with two interactions between fish and environment, are introduced. Based on the simplest scenario, eight different parameter combinations are tested. Then the optimization problem is solved for each of the 6 scenarios for a period of 100 years in order to gain long term insights. The main finding is that higher volatility from the environment leads to higher net profits but together with a lower probability of actually hitting the mean values. Simulations are conducted with different fixed fishing mortality levels under 6 scenarios. It seems that a constant fishing mortality around 0.06 is optimal. In the end, a comparison is made between historical and optimal harvest for a period of 40 years. It turns out that in more than 70% of the time, the optimal exploitation offered by our optimization model dominates the historical one, leading to 43% higher net profit and 34% lower fishing cost on average.

1 Introduction

Many economic fishery studies have described the state of a population using biomass as the only variable [1]. Such surplus production models use lumped parameters to describe the stock dynamics. In recent years, fishery biologists and economists widely begin to recognize that such one-dimensional models are too simple for developing realistic management guidelines [2]. One concern is about the dangerous tendency to catch small and immature fish [3]. Another is that ever increasing fishing pressure may cause various systematic changes in the internal structure and evolution of

fish populations [4], which may have crucial economic consequences that can not be captured by the biomass approach. The age-structured framework is pioneered by Baranov (1918) [5], Beverton and Holt (1957) [6], and Leslie (1945) [7] among others. Many extensions have been explored since and have dominated fishery management (2001) [8]. However analyzing the problem technically is still challenging. Clark has pointed out that an analytical solution for the general age-structured problem is unattainable [9]. Many models lend themselves to Mathematical Programming (Operational Research) and simulations, but not much to analytical studies. Still it is possible to formulate a proper model and simulate how different factors influence the optimal fishing mortalities numerically. Our model is inspired by, among others, Walters (1969) [10], Hannesson (1975) [11], Getz and Haight (1989) [12], Horwood(1987) [13] and Tahvonen (2009) [14].

NEA (Northeast Atlantic) Mackerel (*Scomber scombrus*) is a fish species with high commercial values. In the 1960s and 1970s, the annual catches of mackerel in the Northeast Atlantic, mainly North sea, rose steeply, resulting in an extreme drop in the 1980s. Consequently the mackerel stock has been at low level for many years with poor recruitment. ICES (International Council for the Exploration of the Sea) advices have been proposing limits on the fishing mortality or the size of the catch to improve the situation of the unsustainable harvest. But still in 2014, as in all years since 2008, unilateral quotas have been set higher than the TAC indicated by the ICES Management Plan [15]. It is thus of high interest to investigate the management of NEA mackerel.

Among many environmental factors, food availability can be crucial and representative for all species. As typical plankton feeders, mackerel is affected by the abundance, distribution and composition of zooplankton to a large extent [16]. Most zooplankton species have a life span shorter than one year, thus no age structure is applied for the zooplankton population. The characteristics such as density, average size and distribution of zooplankton that interact with the mackerel stock are many. In order to reasonably simplify the problem, a single *zooplankton index* is used to describe prey density or the food availability for mackerel. Note that due to the position of zooplankton as a primary producer in the low trophic level, several assumptions are implied, which may or may not fall into the category of standard predator-prey models [17]. First, the consumption of zooplankton by mackerel this year will not influence the prey density next year. Due to the many predators that zooplankton has simultaneously, the sole impact from mackerel is difficult to quantify. Second, the food supply of mackerel depends entirely on zooplankton abundance. Other prey species are not included.

Random variations in the environment affect the dynamics of populations through changes in individual life histories [18]. In this article two interactions between the environmental factor (zooplankton index) and the fish population (mackerel) are considered. The first interaction is the influence by the zooplankton abundance on the mackerel recruitment. Mackerel spawns between May and July, which coincides with the zooplankton boom [19]. It is known that higher food availability can bring down the natural mortality especially of the small fish larva by allowing them to spend more time in the deeper, darker and safer area of the sea. Since this interaction mainly applies for the first year juveniles, it can be translated to a constant natural mortality plus a varying recruitment influenced by the zooplankton abundance. The reason for the second interaction is the strong and positive connection between weight and price. On the final product market, a mackerel can be called 'large size' if the average weight is 400 to 600 gram (4-6 category); 'small size' if the average weight is 200 to 400 gram (2-4 category). The price differences between categories can be huge. Assuming one price for all age classes may not be realistic.

There have been different approaches dealing with the two interactions: recruitment and weight. To deal with recruitment, some have chosen an exogenous and constant recruitment such as Beverton and Holt (1957) [6], Clark (2010) [9] while some have assumed that recruitment can be endogenous and stock-dependent such as Walters (1969) [10], Getz and Haight (1989) [12]. In this article both approaches will be applied. To deal with weight, some studies such as Walters (1969) [10] referred to the *von Bertalanffy* function as the rule which decides the individual fish weight. This article links mackerel's annual weight gain to the exogenous zooplankton index, which can either be deterministic or stochastic for different scenarios.

Due to its complexity, the age-structured model can be sensitive to many parameters [13]. It is thus necessary to be cautious with different parameter combinations. In the literature, one issue has been connected to the parameter sensitivity: the optimal choice between smooth and stable harvesting over time and periodic (oscillatory or pulse) fishing [20]. Clark argued in his book that when there exists perfect selectivity, it is optimal to harvest each cohort at its maximum biomass, creating a stable harvest strategy [9]. Hannesson (1975) [11] pointed out that non-selective gear leads to pulse fishing. He also showed that discounting shortens the intervals between fishing periods. Tahvonen (2009) [14] proves that when there are 2 age classes with endogenous recruitment, optimal harvesting is pulse fishing under specific conditions such as non-selective gear. Steinshamn (2011) [21] showed that pulse fishing becomes less attractive as the distribution of the species moves from uniform to schooling. Rocha et.al (2012) [22] concluded that imperfect selectivity increases

the optimal lifespan and the optimal pulse length. In this article, before introducing the stochastic environmental factor into the model, various parameter combinations are explored in order to obtain reasonable assumptions.

There are many innovative contributions of this article. First, while many predator-prey models have been focusing on higher trophic levels, for example predator-prey relationship between two fish species [23, 24], this article instead investigates the lower trophic level including primary production. Second, introducing a volatile zooplankton index as a representative of the environmental stochasticity serves the purpose of realistic assumption as well as innovative approach. Third, a complete series of eight parameter combinations have been examined before introducing the random environmental interactions. Fourth, based on a common framework of the model, 6 different scenarios have been applied in order to fully investigate the problem. Last but not least, based on the same population dynamics, both simulation and optimization are conducted, offering deeper understandings of the problem with the same population dynamics. With the above mentioned traits, we hope that this work can bring new insights and interesting results into the current literature.

In section 2, we illustrate the basic model, the two interactions between the fish population and the environmental factor and 6 different scenarios. In section 3, by varying three parameters, all eight parameter combinations are explored and analyzed. In section 4, the optimization model is solved for all 6 scenarios and the results are summarized. In section 5, simulation is conducted for all 6 scenarios with varying fishing mortality values. Both net profit and harvest biomass are plotted against fishing mortality. In section 6, the historical harvest from data and the optimal harvest from the model are simulated and the results are compared.

2 Model illustration

2.1 Model formulation

The population dynamics is:

$$x_{a+1,t+1} = x_{at}e^{-(m_a+s_{at}f_t)}, a = 0, 1, \dots, n-1; t = 1, 2, \dots, T-1 \quad (2.1)$$

where x_{at} is the number of fish individual of age a at time period t measured in millions; x_{a1} is given by historical data as the initial status of the stock; m_a is the natural mortality; f_t indicates the fishing mortality at period t as the final decision variable and s_{at} is the selectivity parameter. The dynamics indicates that every year

part of the cohort dies out of natural causes and another part is being harvested. Both events are assumed to happen instantaneously. The rest is assumed to survive the year and continue to grow and reproduce. The maximum age of mackerel in the model is denoted by n and T indicates the end period. It is assumed that all fish above age n will naturally die.

In order to describe the recruitment, the Spawning Stock Biomass (SSB) is calculated as following:

$$S_t = \sum_a u_a x_{at} w_{at} \quad (2.2)$$

where S_t is the SSB at time t measured in million tonnes; u_a is the maturity ogive (proportion of sexually matured individuals in that age class) and w_{at} is the individual weight of the fish for age class a at time t .

The endogenous recruitment can be generalized as

$$x_{0,t+1} = \varphi(S_t), t = 1, 2, \dots, T - 1 \quad (2.3)$$

where φ is a recruitment function.

Harvest can be obtained from the well-known Beverton-Holt [9] model:

$$H_t = \sum_a \frac{s_{at} f_t}{s_{at} f_t + m} (1 - e^{-(m_a + s_{at} f_t)}) w_{at} x_{at} \quad (2.4)$$

$$h_{a,t} = \frac{s_{at} f_t}{s_{at} f_t + m} (1 - e^{-(m_a + s_{at} f_t)}) w_{at} x_{at}$$

where H_t is the harvest biomass measured in million tonnes at time t and $h_{a,t}$ is the harvest biomass measured in million tonnes at time t for age class a .

The problem's objective is to maximize the following:

$$\max_{f_t \in F} Z = \max \sum_t (1 + r)^{-t} \left(\sum_a p_{at} h_{a,t} - c f_t \right) \quad (2.5)$$

where Z is the present value of net profits for the whole period; r is the discount rate; p_a indicates the unit weight price for age class a at time t and c is the cost parameter.

The objective function is subject to the following constraints:

1. Population dynamics: Equation 2.1.
2. Sustainability constraint: SSB does not fall below a proposed reference point in the end period:

$$\sum_a u_a w_{aT} x_{aT} \geq B_{lim}, a = 0, 1, \dots, n \quad (2.6)$$

3. Non-negativity:

$$x_{at} \geq 0, a = 0, 1, \dots, n; t = 1, 2, \dots, T \quad (2.7)$$

4. Effort restriction (admissible controls defined by harvest capacity): fishing mortality lies within a certain range:

$$f_t \in F, t = 1, 2, \dots, T \quad (2.8)$$

The problem is solved in GAMS as a nonlinear programming problem using solver NLP.

According to Steinshamn (2011), the stock elasticity parameters for different fish species vary, resulting in various population dynamics and production functions [21]. The model is concise and easy to analyze in the extreme cases where stock elasticity equals either zero or one. Zero stock elasticity lend itself to pure schooling fishery where production function is independent of the stock. Mackerel, which has a certain schooling behavior, has a stock elasticity between zero and one. A larger stock level, even for schooling species, naturally leads to higher probability of finding the fish schools given the same level of searching effort. Thus we believe the production function is not stock independent. Also another study of a schooling species Norwegian Spring-Spawning Herring uses a similar model as in this article [25]. Thus we simply apply a stock elasticity of one in the model.

In accordance with this, we follow that $f = qE$ where q is the catchability parameter [9]. Optimizing with respect to fishing mortality is then equivalent to finding the optimal effort. The cost parameter c in the model can also be understood as the unit cost of effort multiplied by the catchability parameter.

2.2 Two interactions

Here we introduce the zooplankton index ρ_t as first mentioned in Section 1. It is assumed to take the form of a Bounded Random Walk (BRW) as follows [26, 27, 28]:

$$\rho_{t+1} = 0.01[100\rho_t + e^{-120}(e^{-3(100\rho_t-100)} - e^{3(100\rho_t-100)}) + \sigma_\rho \varepsilon_t] \quad (2.9)$$

where ε_t is a sequence of independent and identically distributed (i.i.d.) random variables with $E[\varepsilon_t] = 0$ and $Var[\varepsilon_t] = 1$. The zooplankton volatility σ_ρ determines

the level of randomness and here $\sigma_\rho = 2$. This process has a mean reverting property around 1 but behaves like a random walk in the range of $[0.6, 1.4]$. Another constraint of $\rho_t \in [0.5, 1.5]$ is applied in order to avoid values outside the range.

The first interaction of the zooplankton influencing mackerel's average weight gain goes as follows:

$$w_{a+1,t+1} = w_{at} + [0.036(\rho_t - 1) + 0.055], a = 0, \dots, n - 1; t = 1, \dots, T - 1 \quad (2.10)$$

$$w_{0,t} \approx 0, t = 1, \dots, T$$

Usually growth rates are difficult to determine from catches because schools are sorted by size and their mobility prevents representative sampling [29]. There is a small difference between weight of catch and weight of stock in the data, but this is ignored in our model. It is also assumed that the weight for the first age class is virtually zero. As the same cohort accumulates its weight over time, the zooplankton index ρ_t decides how much weight is gained each year for all cohorts.

When $\rho_t = 1$ for all t , weight gain is assumed to be constant every year since the average age-specific weight has such property as shown in Figure 1.

$$w_{a+1,t+1} = w_{at} + 0.055, a = 0, \dots, n - 1; t = 1, \dots, T - 1 \quad (2.11)$$

In this case, the weight development for each cohort can also be written as a linear function of time:

$$w = 0.055t, t = 1, \dots, T \quad (2.12)$$

The possible maximum and minimum individual weights respectively are 0.83 kg and 0.49 kg at the age of 12 in the model. There exists extreme cases where maximum weight is reported to be 3.5 kg [30]. Such outliers will not be considered in the model.

The second interaction is about zooplankton influencing mackerel's recruitment. Under different scenarios, recruitment can be: first, exogenously given and fixed as 4500 millions; second, governed by a recruitment function; third, exogenous and random from a normal distribution $N(4500, 2000)$ according to historical data from 1980 to 2014 [15]. For the second case, we choose the Ricker formula [31], i.e.

$$\varphi(S_t, \rho_t) = \rho_t \alpha S_t e^{-\beta S_t} \quad (2.13)$$

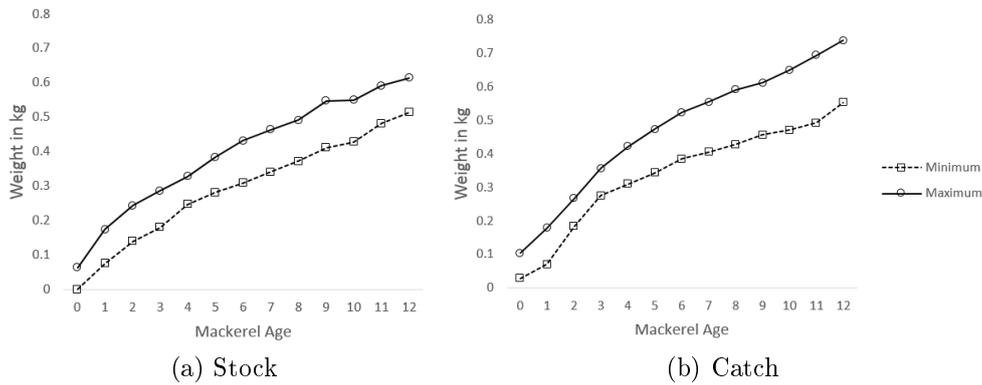


Figure 1: Minimum and maximum weight of mackerel by age class from year 1980 to 2014

where $\alpha = 6.37$ and $\beta = 0.52$ for NEA mackerel [32].

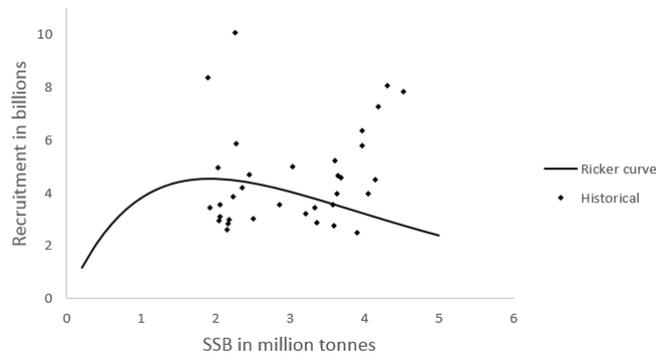


Figure 2: Ricker recruitment function and the historical recruitment data

It can be seen from Figure 2 that the historical recruitment data (square dots) have very high volatility and spreads widely around the curve. The recruitment curve has limited explanatory power about the relationship between the SSB and the recruitment next year.

2.3 Scenario illustration

The zooplankton index can either be deterministic and fixed as 1 (denoted as D) or stochastic as a BRW process as in Equation 2.9 (denoted as S). On the other hand, recruitment can be fixed as 4500 millions (denoted as F) or governed by recruitment curve as in Equation 2.13 (denoted as C) or random from a normal distribution $N(4500, 2000)$ (denoted as R). All scenario combinations are listed in Table 1. In scenarios DF, DC and DR, weight gain is governed by Equation 2.11 while in scenarios SF, SC and SR by Equation 2.10.

Recruitment	Zooplankton index	D	S
	Fixed	DF	SF
	Curve	DC	SC
	Random	DR	SR

Table 1: Scenario illustration

3 Parameter

This section applies scenario DF where the zooplankton index is deterministic as 1. Recruitment is assumed to be constant as the historical mean from 1980 to 2014 [15]:

$$x_{0,t} = 4500, t = 2, 3, \dots, T \quad (3.1)$$

Weight development for each cohort is assumed to be linear in time as in Equation 2.12.

3.1 Parameter choices

It is common practice to assume the age classes of mackerel are from 0 to 12, where the 0 age class is the recruitment of that year. So $a \in [0, 1, 2, \dots, 12]$ and $n = 12$.

The whole modeling period is set to be 100 years in order to gain long term insights of the problem. Thus $t \in [1, 2, \dots, 100]$ and $T = 100$. The original status of the stock for each age class in the model comes from the data in year 1980. Discount rate r is 5%.

The effort constraint can be chosen as the following which has a high enough upper bound for fishing mortality [13].

$$f_t \in [0, 10], t = 1, 2, \dots, 100 \quad (3.2)$$

Fishing costs c is calibrated to 23000 in order to obtain a cost-revenue ratio around 70%: a number that has been observed for pelagic fisheries such as mackerel, herring, blue whiting and capelin [33]. Minimum SSB is B_{lim} is 1.84 million tonnes [15]. Maturity ogives of mackerel u_a are presented in Table 2. The three varying parameters are price, selectivity and natural mortality. We can either apply a constant number, which is usually what has been done, or utilize the age structure of the model by assigning age-specific or weight-dependent parameter values, which can be more realistic.

Price of mackerel p_{at} in norwegian kroner per kilogram (NOK/kg) is either con-

stant as the mean price of 8.46 NOK/kg or linear as a function of weight [34]

$$p_{at} = 19.87w_{at}, a = 0, \dots, n; t = 1, \dots, T \quad (3.3)$$

Selectivity s_{at} is assumed to be either knife-edge selective (denoted s'_{at}) where only classes above a certain age are harvest or non-selective (denoted s^*_{at}) where every age class lend itself to some natural mortality. Both are shown in Table 2. According to ICES report [15], there has been a slow shift from selecting older classes to younger classes over time. Note that age-class zero is of no interest for harvesting. s^*_{at} can be calculated as the age specific fishing mortality divided by maximum fishing mortality in the same year. It is the average value for the first 35 years and is used as year 35 for the remaining periods.

Natural mortality of mackerel m_a is assumed to be constant as 0.15 for all age classes [15] or age-specific as:

$$m_a = 0.32 - 0.02a, a = 0, 1, \dots, 12 \quad (3.4)$$

Age	u_a	s'_{at}		s^*_{at}	
		$t \in [1, T]$	$t \in [1, 35]$	$t \in [36, T]$	$t \in [36, T]$
0	0	0	0.03	0.01	
1	0.106	1	0.1	0.04	
2	0.539	1	0.18	0.18	
3	0.913	1	0.37	0.43	
4	0.998	1	0.64	0.72	
5	0.999	1	0.73	0.82	
6	0.999	1	0.9	0.83	
7	1	1	1	1	
8	1	1	1	1	
9	1	1	1	1	
10	1	1	1	1	
11	1	1	1	1	
12	1	1	1	1	

Table 2: Parameter values for price, maturity ogive and selectivity

3.2 Parameter combinations

The three varying parameters are combined and explored: constant vs. weight-dependent price; knife-edge selective vs. non-selective; constant vs. age-specific natural mortality. This gives a total of eight combinations. It is found that the results are highly sensitive to parameter assumptions. In other words, a small change in parameter combination may lead to very different results.

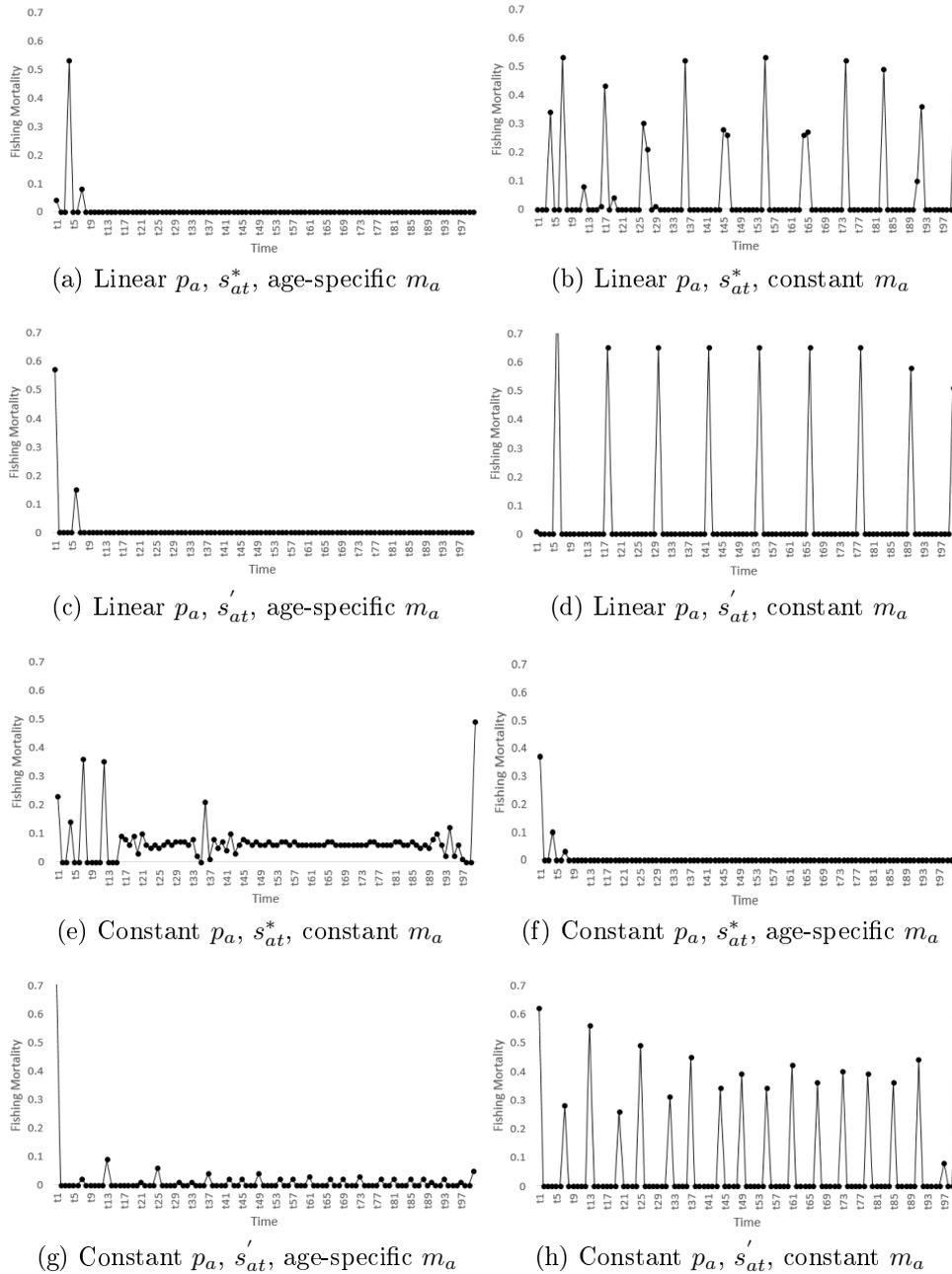


Figure 3: Optimal fishing mortality for all parameter combinations

It is found that weight-dependent price, knife-edge selectivity and constant natural mortality lend themselves to pulse fishing. A possible explanation is that the weight-specific price structure puts higher value on older classes, justifying the waiting period before harvesting. With selectivity s'_{at} , younger age classes are more vulnerable towards harvesting and this creates a relatively lower fishing pressure for the older age classes. Selectivity parameters applied have in fact very limited difference: s^*_{at} is the same as s'_{at} above age 7. But it induces large influence of the final result. This article numerically illustrates the scale of the issue, which should never be underestimated. In many cases, natural mortality is assumed to be constant for all. When the bigger fish is assumed to have a higher probability to survive, this also gives incentive to wait for the stock to accumulate. To sum up, any parameter choice that favours the older age classes, for example by assigning higher value or decreasing the chance of death of older classes, tends to lend itself to pulse fishing pattern.

4 Optimization under different scenarios

In this section, we choose the parameter combination as: price is weight-dependent, selectivity is s^*_{at} and natural mortality is a constant. This combination has a modest tendency towards favour pulse fishing pattern. All other parameter values are as in Section 3. All scenarios in Table 1 will be explored and summarized in this section.

4.1 Mean results

For scenario SF, SC and SR, 1000 possible outcomes of the environmental factor, zooplankton index, are drawn randomly. Each represents a possible scenario of the environmental development path during 100 years. The model is treated as a deterministic nonlinear programming problem under each path. Optimization is conducted for each scenario.

The indicators of the results are explained here. Net profits Z and fishing costs C are measured in million dollars and calculated as the mean from the 1000 scenarios. The average time series of harvest \overline{H}_t and stock biomass \overline{B}_t are measured in million tonnes and are obtained as the average from the 1000 scenarios. \overline{H} , \overline{B} and $\overline{x}_{0,t+1}$ are the average harvest, stock biomass and recruitment respectively. Only periods from $t18$ to $t90$ are used to calculate the mean results in order to avoid the adjusting phases in the beginning and at the end of the model, which have very high volatility. σ_Z^* denotes the standard deviation of the sample for net profits and σ_C^* denotes the

standard deviation of the sample for fishing costs.

Scenario	DF	DC	DR
Indicators			
Z	12504	8761	14222
C	29817	23733	30843
σ_Z^*	/	/	1497
σ_C^*	/	/	1884
\bar{H}	0.2	0.1	0.22
\bar{B}	5.17	4.15	5.16
$\bar{x}_{0,t+1}$	4500	3308	4509

Table 3: Mean results for scenario DF, DC and DR (Z and C are net profit and fishing cost for the whole period. σ^* represents the standard deviation of the sample. \bar{H} is the average harvest in million tonnes. \bar{B} is the average stock biomass in million tonnes. $\bar{x}_{0,t+1}$ is the average recruitment in millions. Average values are obtained from $t18$ to $t90$.)

As illustrated in Table 3, for scenarios DF and DR, the only modeling difference is the randomness of recruitment. Scenario DR has higher profit and cost on average but with a lower probability of actually reaching the mean value. Note that random recruitment in scenario DR is from a symmetric probability distribution around the same mean as DF. The model seems to be able to efficiently capture and utilize the extremely high recruitment to reach higher average profits. It is also noticeable that σ_C^* is generally larger than σ_Z^* . This may be explained by the way fishing costs and sales revenues are calculated. On one hand, many elements are involved in determining the sales revenue such as individual weight and stock size, thus smoothing out potential variances. On the other hand, the calculation of total fishing cost is purely linked to fishing mortality, which may have high volatility. Scenario DC results in the lowest net profit, lowest cost and poorest harvest and stock biomass. In more than 99% of the time, scenario DC reaches a lower net profit than DR. This is mainly due to poor recruitment. With the fact that recruitment data usually have very high volatility, letting a single recruitment function to take over seems an unreliable and pessimistic scenario.

When comparing Table 3 and 4, all three scenarios have similar results to its counterparts. Compared to DF, scenario SF has a higher mean net profit and much higher σ_Z^* and σ_C^* , which is mainly caused by varying annual weight gains. This implies that when recruitment is fixed, the randomness of weight gain, which is pre-

Scenario	SF	SC	SR
Indicators			
Z	12955	9491	14596
C	29954	24442	30821
σ_Z^*	2228	1851	2811
σ_C^*	2860	4199	3164
\bar{H}	0.19	0.13	0.23
\bar{B}	5.19	4.14	5.16
$\bar{x}_{0,t+1}$	4500	3290	4498

Table 4: Mean results for scenario SF, SC and SR (Z and C are net profit and fishing cost for the whole period. σ^* represents the standard deviation of the sample. \bar{H} is the average harvest in million tonnes. \bar{B} is the average stock biomass in million tonnes. $\bar{x}_{0,t+1}$ is the average recruitment in millions. Average values are obtained from $t18$ to $t90$.)

sumably small, is transferred to the volatility of the value as well as cost of harvesting. Similar to DC, scenario SC has a poor performance: in more than 70% of the time, scenario SC leads to lower profits than SR. However scenario SC has a higher net profit than DC on average due to the introduction of random environmental factor. Scenario SR, similar to DR, has the highest profit and cost on average among the three. The varying annual weight gain almost doubles σ_Z^* and σ_C^* by switching from DR to SR.

To sum up, higher volatility of the zooplankton index, implying either varying recruitment or volatile weight gains, leads to higher net profits on average but together with a lower probability of actually hitting the mean values. It can be interpreted as the risk of the fishing industry brought by nature. When recruitment is fixed, volatile weight gains cause considerable increase of σ_Z^* and σ_C^* . When weight gain is constant, random recruitment also lends itself to larger volatility of profits and costs. Strong and extremely good recruitment can be utilized by the model to reach higher profits. Net profits usually have smaller variances than fishing costs mainly due to the structure of the model. Recruitment governed by a recruitment function tends to lead to the weakest zero age-class, thus the poorest overall performance.

4.2 Time serie results

Figure 4 presents the mean estimated optimal fishing mortality time series of 1000 realizations under each scenario. Scenarios DF, DC, SC and SF generate different scales of pulse fishing pattern while DR and SR have a more smooth and stable harvest. A possible explanation for the smooth harvest under scenario DR and SR lies in the random recruitment. In scenario SC, the volatility of simulated recruitment is roughly 600 while in DR and SR it is 2000. When the volatility of recruitment is within a certain range, the pulse patter still overlaps after taking the average as in SC and SF. But as the volatility continues to increase, the optimal harvest still has pulse pattern but becomes much more scenario-specific, so taking the average will smooth it out to a more stable pattern. It is stated before that the combination of parameter choices greatly influence the optimal fishing pattern. This reveals that no matter whether recruitment is given as a fixed number or exogenously influenced by a varying index or stock-dependent from some recruitment curve, the model tends to give pulse fishing patterns as long as it is deterministic under certain parameter combinations. When comparing DF with DC or SF with SC, it is shown that more abundant recruitment will shorten the waiting period between harvests.

5 Simulation

A very straightforward policy in real life is a constant fishing mortality. In this section, fishing mortality from 0.02 to 0.1 is assessed through simulations of the stock in 100 years under different scenarios. All parameters are the same as in Section 4.

As shown in Figure5, regardless of the choice of scenarios, net profit is maximized when fishing mortality is around 0.06. Another study about the Norwegian spring spawning herring (NSSH) finds that with a time horizon of 20 years, a constant fishing mortality of 0.15 is economically optimal [35]. Note that in this study a much shorter time horizon is applied and the price of the fish is assumed to be a constant. In the management plan simulations of ICES advice 2015, the NEA mackerel stock is simulated with different target fishing mortalities from 0.2 to 0.35. No economic elements are involved in these simulations. It seems that our simulations end up with relatively low fishing mortality levels. One possible explanation is the weight-specific price structure used in our study. This not only makes sure that crucial economic aspects are considered but also becomes a more realistic assumption than a constant price.

In addition, the level of profit seems to be influenced mainly by the mean re-

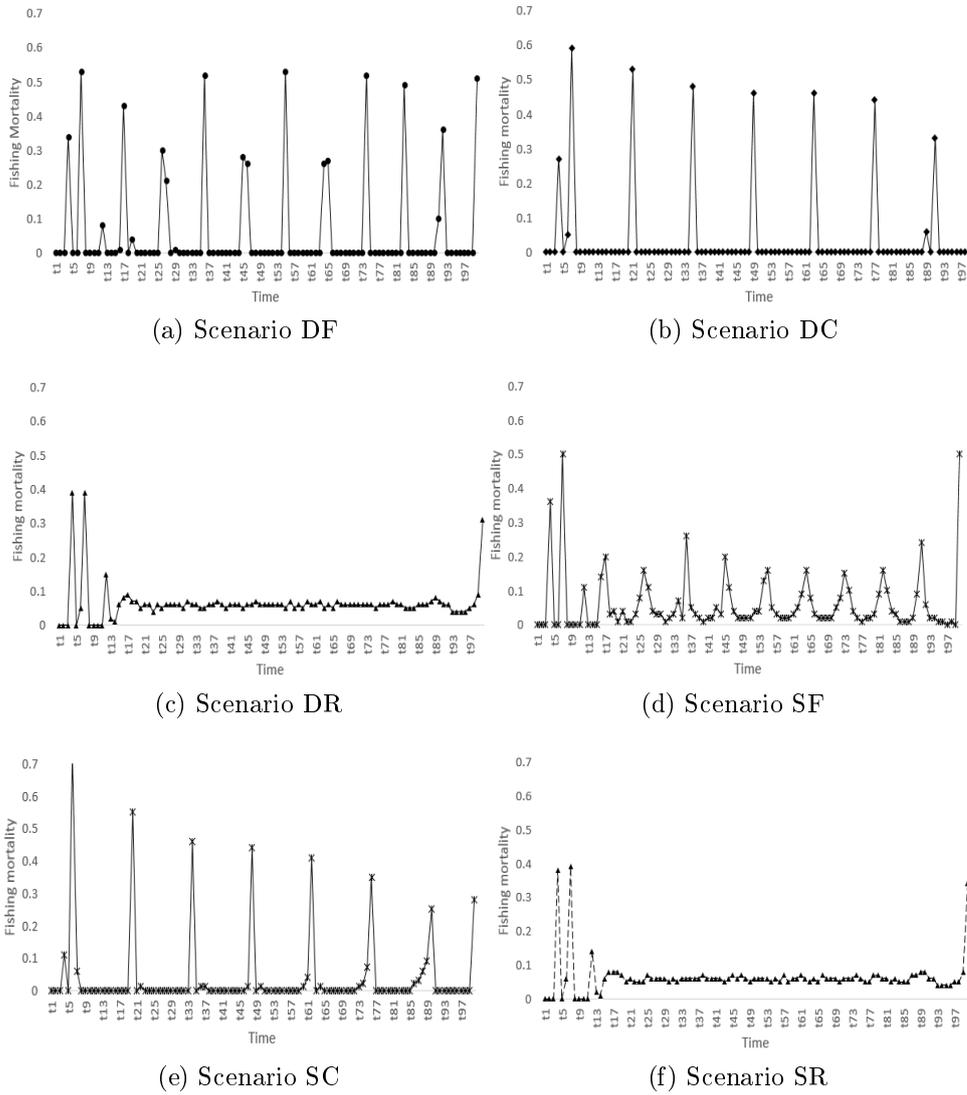


Figure 4: Estimated optimal fishing mortalities

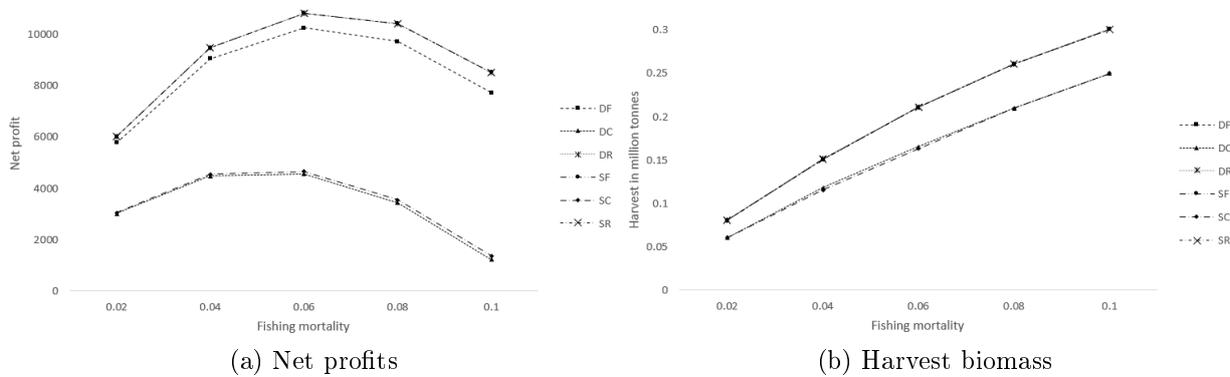


Figure 5: Simulated net profits and harvest biomass with different fishing mortality under each scenario

recruitment and the random environmental factor. In scenario DC and SC where recruitment is determined by the Ricker function, the mean recruitment is significantly lower, leading to smaller profits and smaller optimal fishing mortality. In the rest of scenarios, DF is the only scenario without any uncertainty involved and has the lowest profits. It may be a bit counter-intuitive that when a constant harvest is applied, a scenario with very stable environment is dominated. But this agrees with the findings from section 4.1. Compared to Table 3 and 4, simulations lead to average profits that are at least $1 \sigma_Z^*$ lower than the optimization models.

It can also be seen that the function of harvest against fishing mortality is concave: as fishing mortality increases harvest also rises but with a lower speed. Since the fishing mortality is kept constant for years in the simulation, a heavier harvest corresponds to a smaller stock in general. If the fishing mortality is even higher, large fishing effort will have little return due to low stock level.

6 Historical vs. optimal harvest

After both optimization and simulation under the 6 different scenarios in Section 4 and 5, it is of interest to apply some real data to the model and make comparison between historical harvest and optimal harvest offered by the optimization model. This section assumes that the zooplankton index is stochastic and recruitment is governed by a recruitment curve as in Equation 2.13, in order to fully capture the two interactions of recruitment and weight gain. Fishing cost c is adjusted to 11000. Parameter T is changed to 40 years in order to cover the available data from 1980 to 2014. The fishing cost C for the whole period is calculated as:

$$C = \sum_t (1+r)^{-t} c f_t \quad (6.1)$$

We use ' H ' to indicate the results of *historically* applied harvest and ' O ' for the *optimal* harvest. Both have the same random number generator seed. In order to create realistic proposals, an extra constraint of Equation 6.2 is added, where $k_1 = 0.75$ and $k_2 = 1.25$ are the minimum and maximum annual change rate respectively from historical data.

$$k_1 \leq \frac{f_{t+1}}{f_t} \leq k_2, t = 1, \dots, T-1 \quad (6.2)$$

As shown in Table 5, H leads to 43% lower profit, 34% higher cost and a larger cost-revenue ratio on average. In addition, with more than twice the fishing mortality

Indicators	H	O
Z	15944	28216
C	47309	31067
σ_Z^*	4080	2769
σ_C^*	396	388
\bar{H}	0.44	0.28
\bar{B}	2.76	3.63
$\bar{x}_{0,t+1}$	4369	3778
\bar{f}	0.312	0.118

Table 5: Results for H and O (Z and C are net profit and fishing cost for the whole period. σ^* represents the standard deviation of the sample. \bar{H} is the average harvest in million tonnes. \bar{B} is the average stock biomass in million tonnes. $\bar{x}_{0,t+1}$ is the average recruitment in millions. \bar{f} is the average fishing mortality. Average values are obtained from $t15$ to $t35$.)

and 1.6 times the harvest biomass of O , H maintains 32% lower stock biomass level. The historical harvest is economically inefficient and biologically unsustainable.

As presented in Figure 6, it is no surprise that the estimates of H show that NEA mackerel stock had been harvested unsustainably. The stock biomass kept decreasing to a minimum level around 2.4 million tonnes in year 2005. In year 1994 and 2003, fishing mortality peaked to 0.37 and 0.46 respectively. After the second peak, fishing mortality came down to around 0.22, leading to a slight recover in stock biomass.

The fishing mortalities in Figure 6b can be the proposal for managing plans of the NEA mackerel from our model. It not only leads to higher net profit but also a higher and more stable stock biomass, which is crucial for long term, sustainable fishery resource management. The proposed exploitation strategy secures both biological and economical potential of the stock, diminishing the possibility of potential population collaps.

In addition, as Hannesson (2011) [36] pointed out '*What pulse fishing means is that a stock of fish is fished down heavily for a short period of time and then left to replenish itself for a longer period. But what does the industry do in the meantime?*' The constraint from Equation 6.2 leads to limited variations of fishing mortality over time. It is shown in Table 6 that as the constraint gets tighter, both profit and cost tend to decrease; the shadow cost for having the constraint rises. Still, the scale of the constraint shadow cost is low: within 10%. At a relatively low cost, the constraint has made the proposal more realistic since stable quotas are favored by fishermen

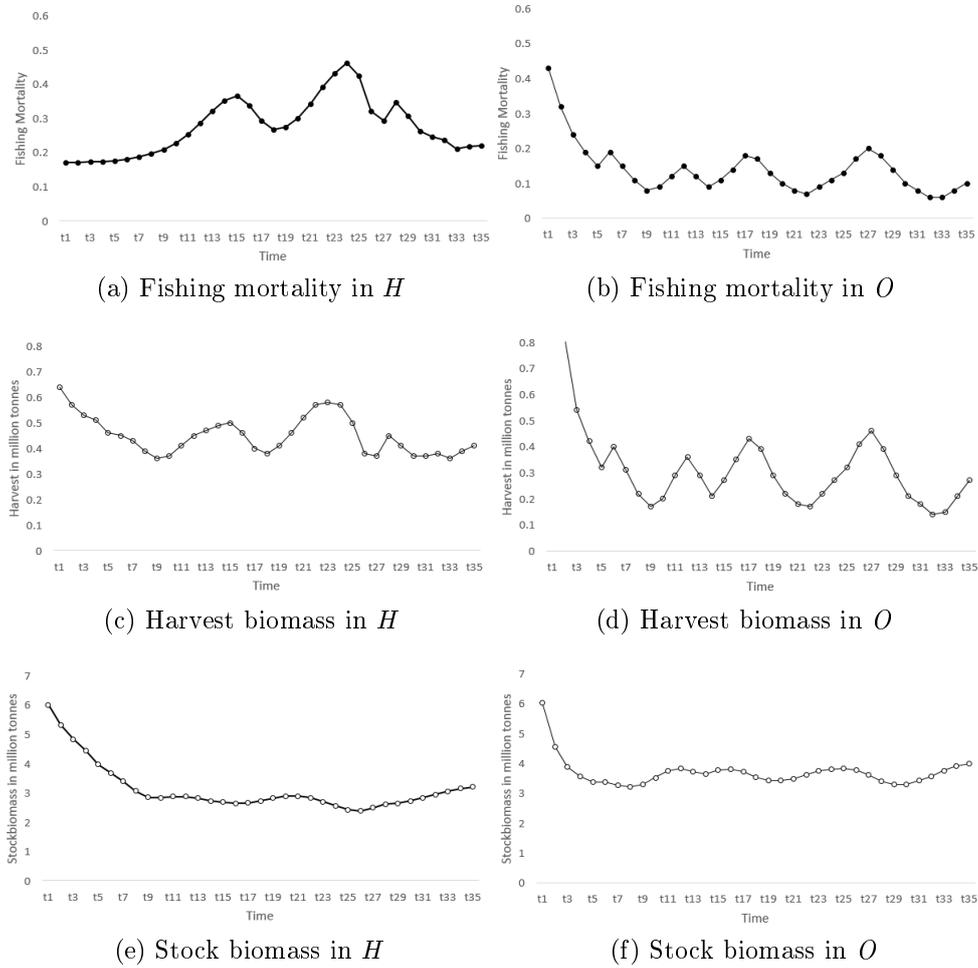


Figure 6: Results for scenario H and O

Parameter sets	1	2	3	4	5
k_1	0.75	0.9	0.95	0.98	$+\infty$
k_2	1.25	1.1	1.05	1.02	$-\infty$
Z	28216	27934	27512	26894	29332
Shadow cost	3.8%	4.8%	6.2%	8.3%	/
C	31067	30451	30547	30209	31770
σ_Z^*	2769	2748	2825	2942	2903

Table 6: Results for O under different sets of k_1 and k_2 (Z and C are net profit and fishing cost for the whole period. Shadow cost is calculated as the percentage difference of the objective value Z with (set 1-4) and without (set 5) the underlying constraint. σ^* represents the standard deviation of the sample.)

as they enable the decision making to be more predictable and correct. When the annual change rate of fishing mortality is within 2% ($k_1 = 0.98$ and $k_2 = 1.02$), it is still valid that in more than 70% of the time, O results in higher average net profits than H . It seems possible to obtain better results if the harvest strategy is simply to apply a constant fishing level. Such a strategy has limited risk, higher mean profits and more straightforward implications for the sector.

7 Conclusion

This article investigates the effects of random environmental impacts on optimal harvest of a fish population, which is NEA mackerel in our case. First, we introduce a basic model structure and 6 different scenarios dealing with two interactions. In addition, eight different parameter combinations are tested under the simplest case. It is found that weight-dependent price, knife-edge selectivity and constant natural mortality lend themselves to pulse fishing pattern as the optimal harvest. A proper parameter combination is fixed for the rest of the article.

Then the optimization problem is solved for each of the 6 scenarios for a period of 100 years. The main findings are: higher volatility of the environmental factor leads to higher net profits on average but together with a lower probability of actually hitting the mean values; when one of the two interactions is fixed, the other will cause considerable increase of σ_Z^* and σ_C^* ; strong recruitment can be utilized by the model to reach higher profits; σ_Z^* is usually smaller than σ_C^* mainly due to the structure of the model; recruitment governed by a recruitment curve tends to lead to the poorest recruitment and performance. Simulations are applied with different fixed fishing mortality levels under 6 scenarios. It seems that a constant fishing mortality around 0.06 is optimal. Simulation results are in line with optimization models regarding the effect of environmental randomness. Also the optimization models yield higher net profit on average than simulations regardless of the scenario.

In the end, comparison is made between historical harvest and optimal harvest for a period of 40 years. It turns out that in more than 70% of the time, the optimal exploitation offered by our optimization model leads to 43% higher net profit and 34% lower fishing cost than the historical harvest. Various constraints and the corresponding shadow costs are presented to illustrate that the cost of having limits on the annual change rate of the decision variable is quite small.

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The effects of random environmental impacts on optimal exploitation of a fish population are investigated using both optimization and simulation, based on a discrete-time age-structured bioeconomic model. The optimization problem is solved as a non-linear programming problem in GAMS. First, a basic model structure and 6 different scenarios, dealing with two interactions between fish and environment, are introduced. Based on the simplest scenario, eight different parameter combinations are tested. Then the optimization problem is solved for each of the 6 scenarios for a period of 100 years in order to gain long term insights. The main finding is that higher volatility from the environment leads to higher net profits but together with a lower probability of actually hitting the mean values. Simulations are conducted with different fixed fishing mortality levels under 6 scenarios. It seems that a constant fishing mortality around 0.06 is optimal. In the end, a comparison is made between historical and optimal harvest for a period of 40 years. It turns out that in more than 70% of the time, the optimal exploitation offered by our optimization model dominates the historical one, leading to 43% higher net profit and 34% lower fishing cost on average.

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