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Optimal harvesting of farmed salmon during harmful algal blooms☆

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ABSTRACT

This paper studies the optimal harvesting decisions of a salmon farmer that faces the risk of harmful algal bloom as well as market uncertainty. The salmon farmer seeks to maximize the financial value of the fish farm by determining the optimal course of actions during the algal bloom, and the optimal time to harvest after the bloom. Specifically, we compare the options to perform an early harvest and to wait in order to learn about the true algal risk. We extend this framework by taking into account the option to move the salmon to an algal free location. To illustrate the results and investigate the robustness of our model, we present two case studies with realistic industry parameters from Norway and Chile. We find that there is a significant value associated with the ability of salmon farmers to actively learn about the true risk of losing the biomass. This value is strongly affected by the availability of frequent and reliable information about the algal risk emphasizing the importance of communication between industry actors, as well as facilitation of effective information flow by policy makers and research organizations.

1. Introduction

Harmful algal blooms present a growing global threat to marine aquaculture species. A harmful algal bloom is a rapid increase in the population of algae in aquatic environments that has detrimental effects on aquatic life in that they cause mortality and severe problems with animal welfare and growth, as well as ecology [37]. The frequency and severity of harmful algal blooms have increased dramatically on a global scale in recent decades, and this trend may continue due to climate change [2,55]. There is also consensus among scientists that the resulting economic losses are increasing [3] leading to adverse effects on the coastal communities causing bankruptcies and loss of livelihoods. Thus, better decision-making tools for minimizing economic losses during harmful algal are crucial for a sustainable development of aquaculture industry.

In this paper, we address the problem of managing harmful algal bloom risk from the perspective of salmon farmers. Salmon farming industry has been affected by a large number of dramatic harmful algal blooms globally. For example, in 2016, a severe outbreak in the southern parts of Chile killed 39,000 tons of Atlantic salmon and trout [44]. The risk of losing millions worth of revenues forces small and large salmon farmers to make swift decisions regarding how they should respond to the threat. At the same time, salmon farmers receive information about the algal spread from research communities, as well as hearsay from nearby farms, which creates an incentive to wait in order to learn about the risk and make more informed decisions [23,35]. Although there exists a wide body of literature on optimal harvesting decisions of salmon [5,26], there is a clear lack of studies that explicitly account for the risk of losing the biomass. Among the few contributions that explicitly take into account the impact of diseases on the harvesting decisions is [1] that study lice infestations. However, potential lice impacts differ substantially from the consequences of a harmful algal bloom. This motivates the development of appropriate dynamic decision tools for salmon farmers that explicitly take into account the impact of harmful algal blooms, as well as and the possibility to learn about the likelihood of their occurrence, which we focus on in this paper.

For an harmful algal bloom to take place, there must be enough nutrients and light for it to develop, however, as harmful algal blooms consume the nutrients it will naturally fade out after some time. This makes harmful algal blooms inherently time-limited events. In many cases, it is hard to foresee blooms, the reasons behind them, as well as their total duration. Nevertheless, it is important for fish farmers to take

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immediate action if a harmful algal bloom is reported nearby or if the fish behave abnormally. In this paper, we focus on two potential mitigation strategies that involve reducing the negative impacts of harmful algal bloom: performing an early harvest and/or moving the biomass.

Early harvest entails losing the future growth of the biomass, and the possibility to harvest optimally at a later stage. In addition, the salmon price is increasing in weight class leading to a further loss of revenue by harvesting smaller fish [13]. When harvesting early, the salmon farmer faces a trade-off between securing revenues from the biomass at the current spot price before potential salmon deaths and further growing the fish taking the risk of harmful algal bloom arrival. During the 2019 harmful algal bloom outbreak in Norway, SalMar, for example, decided to harvest 1,000 tons of salmon weeks before the planned schedule.[1] Moving biomass to a different location can be an effective alternative to early harvest in order to secure future biomass growth. This is supported by the findings in [47] that suggest that spatial diversification provides significant risk reduction related to diseases outbreaks. For example, in 2019, Cermaq and Nordlaks were among the companies that chose to move their fish away from the harmful algal bloom to alternative locations [22]. However, transporting fish under higher densities may lead to stress, which can affect feed conversion ratio (FCR) and mortality rate negatively [11,15]. In addition, this action is only available for large enterprises that operate multiple locations (i.e., companies with spatial diversification).

The fundamental problem for farmers during harmful algal blooms is to choose the right action at the right time given that the true likelihood of that the algae arrival at their farms is not known. Once the Norwegian Food Safety Authority and the Directorate of Fisheries are informed about a harmful algal bloom outbreak, several organizations (SINTEF, Akvaplan-niva, and the Institute of Marine Research) are brought in to assist the salmon farmers with analysis of the harmful algal bloom risks. In addition, the Norwegian Meteorological Institute provides forecasts on sea water streams which could bring the harmful algal bloom to new locations [22]. These organizations provide farmers with information regarding the current and forecasted spread and density of the harmful algal bloom. However, the information flow is not organized by a single organization. This means that the salmon farmers receive information from multiple sources at unknown intervals during the harmful algal bloom. Furthermore, due to a high degree of collaboration in the industry during the harmful algal bloom outbreak, the salmon farmers are able to share resources and information with each other [35]. The collaboration and involvement from research organizations gives salmon farmers the opportunity to make better-informed decisions.

Another challenge that the farmers face when making their harvesting decisions is that the price of farmed salmon is uncertain. Several recent studies investigate the salmon spot, forward and futures price dynamics (e.g., [6,17]). They find that innovations in the spot price influence forward and futures prices rather than the other way around, indicating that the salmon futures and forward markets are still immature. It is well established in the literature that the static decision making tools such as discounted cash flow (DCF) analysis may lead to sub-optimal choices when applied to irreversible decisions under uncertainty [41]. Therefore, in order to account for the value of information for salmon farmers, we develop state-of-the-art dynamic real options models to analyze the optimal harvesting decisions in the presence of harmful algal bloom risk. In particular, the salmon farmer is considered to have an option to undertake mitigation measures when facing the risk of harmful algal bloom. The real options approach allows to quantify the value of these options, which represent the benefit of the flexibility to delay irreversible actions in order to gain more information about framework conditions [25,58].

The aim of this paper is, thus, to identify optimal harvesting strategies for small and large salmon farmers when facing the risk of harmful algal bloom arrival and stochastic prices. In order to do so, we develop three real options models. The first model, the General Single Rotation Model (GSR-model), finds the optimal time to harvest while facing uncertain prices without algal risk. The GSR-model quantifies the value of flexibility in the operations of a salmon farmer, and is also used as input into the more advanced models. The Early Harvest Model (EH-model) is the main focus of this paper. The EH-model finds the optimal harvesting strategy and quantifies the value of harvesting flexibility during a time-limited harmful algal bloom. The EH-model also accounts for the imperfect information farmers receive by assuming that salmon farmers learn about the uncertain arrival rate of harmful algal bloom through signals from research organizations. Based on these signals, farmers can actively update their beliefs about the algal arrival rate in accordance with Bayes' rule. The third and final model, the Early Harvest-Move Model (EH-M-model), extends the EH-model and allows companies with spatial diversification to jointly evaluate the decision between early harvesting and moving. We apply the EH-M-model to investigate the option to move the salmon can bring additional value for farmers. We apply the models on two case studies, for Norway and Chile. This is of interest since the world's two largest producers of farmed salmon operate under different production conditions.

The remainder of this paper is organized as follows. Section 2 presents a review of the literature relevant to our research questions. The three models and the solution approaches are described in Section 3. In Section 4, we quantify parameters for a Norwegian and Chilean case study. Results and discussion of the case studies are presented in Section 5. Finally, Section 6 concludes the paper.

2. Literature review

There exists a wide body of literature focusing on optimal harvesting of salmon. Early work analyzes how different costs and growth curves affect the harvesting time, but does not include uncertainties in the model assuming salmon prices to be deterministic [12]. Further work extended this early literature in different directions. Arnason [4] analyzes interdependence of optimal feeding schedule and harvesting time. Later, Forsberg [28] develops a harvesting planning model that has the ability to take all production restrictions into consideration. The harvesting model in Forsberg [28] is later used to find the value of price information, based on different price scenarios by Forsberg and Guttormsen [29]. Forsberg and Guttormsen [29] extend former production planning models to also include forecasting of prices. Asche and Bjørndal [5] add to the existing literature by providing systematic economic analyzes based on more up-to-date Norwegian industry data. In a more recent study, Ewald et al. [26] consider the optimal harvesting problem for both single and infinite production cycle rotations. They build on findings from Asche and Bjørndal [5] and account for stochastic prices in a two-factor price model, using a large set of forwards contracts from Fish Pool exchange market to estimate prices. In line with Ewald et al. [26], we adapt and apply a two-factor price model to our problem using latest price information. Moreover, we follow Asche and Bjørndal [5] on their biomass growth assumptions, to be detailed in Section 3.

None of these studies, however, have accounted for the risk of losing the biomass in the optimal harvesting models. In the aquaculture literature, large efforts have been made in studying causes, detection, and economical impacts of harmful algal blooms rather than their impact on optimal harvesting strategies for salmon farmers (see, e.g., [55,40,33,3,44]). Among the few studies that consider the possible benefits of disease triggered early harvest is [48] in application to pancreas disease (PD). They, however, do not focus on the risk of PD arrival, but rather apply a partial budgeting approach to compare scenarios with and without PD outbreaks inside a sea pen. In their harvesting strategy, they assume that the salmon farmer adopts a diagnostic screening program to monitor the virus levels in the farm. This data is used to forecast a PD outbreak, which for certain thresholds trigger an early harvest to avoid

[1] https://e24.no/boers-og-finans/i/8mOkkG/salmar-slakter-tusen-tonn-laks-for-aa-sikre-seg-mot-alger

disease losses. Unlike in the application of Pettersen et al. [48], salmon farmers facing harmful algal bloom threat can not use a device to monitor algae levels inside the pen, because the salmon dies shortly after the algal arrival.

Another aspect that our paper adds to the existing literature is the possibility to actively learn about the harmful algal bloom risk. Learning within the aquaculture literature often appears in the context of technology uncertainty and adaptation strategies. Several contributions, for example, account for a passive learning-by-doing effect, such as [46,51]. More recent studies incorporate passive learning about key uncertainties in a wait-and-see manner by utilizing real options approach [14,31]. These studies quantify the flexibility to delay the investment decision in new technologies by salmon farmers and by that gather more information about the evolution of key uncertainties. They conclude that the ability to delay the capital expenditure creates a significant value for salmon farmers. Our model, extends this stream of literature by incorporating both active and passive learning in an optimal harvesting problem. The aspect of Bayesian learning has recently gained significant attention in the real options literature. Harrison and Sunar [32] make use of a continuous-time Bayesian framework for updating a firm's beliefs of the unknown project value. Another example is [19] that study how investment behavior in renewable energy is affected by updating a subjective belief on the timing of a subsidy revision. Both [32,19] assume that the signals arrive according to a continuous time stochastic process. Unlike Harrison and Sunar [32] and Dalby et al. [19], Thijssen et al. [57] assume that signals arrive discretely according a Poisson jump process. Thijssen et al. [57] investigate the decision of a firm to invest in a project while receiving imperfect signals about its true profitability. The firm uses these signals to update its valuations of the project and to form a decision rule. Similar to Thijssen et al. [57], we adopt the discrete-time process for signal arrivals. This is because in our problem, signals arrive at irregular intervals, and farmers have free access to the different learning modes (e.g., phone-based information from nearby farmers, reports, and forecasts from research organizations). Moreover, the farmer can neither influence the quality of the information, nor the arrival time of these signals.

More generally, our paper contributes to the extensive literature on the risk management in salmon farming. Several contributions find evidence of a substantial increase in salmon price volatility over the recent years, which creates incentives for the salmon farmers to engage in financial hedging [8,47]. Recently, some studies investigated the salmon spot and forward price dynamics, as well as how financial salmon futures can be used to reduce price risk (e.g., [6,43,53]). In addition to price risks, it is well established in the literature that salmon producers are exposed to significant production risks and are averse to these risks [9,36]. Among the tools that reduce production risk (including diseases, escapes, technical failure) available to salmon farmers are technological investments [14,51,52] and aquaculture insurance [49]. In our model, the salmon farmers reduce the production risk exposure the by active learning about the probability of harmful algal bloom arrival and, as a result, by adjusting their harvesting decisions.

3. The models

In this section, we develop three realistic real options models for the problems of (i) finding the optimal time to harvest in a basic, single production cycle while facing stochastic prices, (ii) finding the optimal time to harvest while also facing uncertain harmful algal bloom arrival risk, and (iii) finding the optimal course of actions when allowing for both early harvesting and moving the biomass.

3.1. General single rotation model

We consider a salmon farmer who seeks to maximize the value of his farm's salmon biomass during a single production cycle. At each point in time, the salmon farmer must decide whether to harvest the fish now or to grow it further. By harvesting the fish, the farmer pays a one-time harvesting cost and receives the revenue from the harvested biomass. The fish farmer will make a profit of $B(t)(S(t)-C_H)$ at the time of harvest, where $B(t)$ denotes total salmon biomass at time t, $S(t)$ is the salmon price at time t, and C_H represents the fixed harvesting cost per kilogram fish.

The total biomass $B(t)$ is the product of the number of fish in the pen, denoted by $R(t)$, and the average individual weight of the fish, given by a weight curve $W(t)$. We denote the number of fish at time $t=0$ by R_0, and assume that $W(t)$ follows a deterministic process described by a von Bertalanffy's growth function,

$$W(t)=w_{\infty}\left(a-be^{-c\left(\frac{t+t_{sea}}{365}\right)}\right)^{3}, \tag{1}$$

where w_∞ is the asymptotic average weight of an individual fish, a, b, and c are constants, and t_{sea} is the time since the fish was introduced to the sea pen. The auxiliary parameter t_{sea} is introduced to study how the optimal strategy is affected by the fish weight at the start of an algal outbreak. The von Bertalanffy's growth function is commonly applied to model fish growth, see for instance (5,26).

Since the salmon is not reproducing in pens, it is common to introduce a fixed mortality rate, M, to model a decreasing number of fish over time. Following [5], we find the number of fish in the pen at time t by solving $R(t)=R_0e^{-Mt}$. Hence, we can estimate the total biomass $B(t)$ at time t by solving

$$B(t)=R(t)W(t)=R_0e^{-Mt}\left(w_{\infty}\left(a-be^{-c\left(\frac{t+t_{sea}}{365}\right)}\right)^{3}\right) \tag{2}$$

As an alternative to early harvest, the salmon farmer can continue growing the fish and potentially receive a higher salmon price in the future, while incurring the production costs $C_p(t)$. We assume that the variable production costs consist of feeding costs only. This is because feeding costs is the main cost driver for salmon farmers during the sea phase accounting for around 50% of the total production costs [7].

The total feed quantity required at time t is the amount of feed needed per fish multiplied with the amount of fish. To find this quantity, we multiply the feed conversion ratio (FCR),[2] f_r, and the weight growth of the fish, $W'(t)$, together with the amount of fish, $R(t)$, i.e., $f_rW'(t)R(t)$. Then for a given feed price per kilogram, C_f, the production costs at time t is $C_p(t)=f_rW'(t)R(t)C_f$..

The optimal harvesting time, τ, of the GSR-model is thus the solution of the following optimal stopping problem

$$F_{GSR}(\tau,S_\tau)=\sup_{\tau}E\left[B(\tau)(S_\tau-C_H)e^{-r\tau}-\int_0^{\tau}C_p(t)e^{-rt}dt\right], \tag{3}$$

where $S(t)$ denotes the salmon spot price at time t. The first term in (3) represents the cash flow received from selling the biomass at the optimal time, less the cost of harvesting, discounted to time zero. The second term is the discounted production costs paid from time zero to the optimal harvesting time, τ. In (3), $S(t)$ denotes the salmon spot price at time t.

In line with [54], we use the two-factor model for simulations of salmon spot prices. In particular, we decompose the logarithm of the salmon spot price into the sum of two stochastic factors, i.e.,

$$\ln(S(t))=\chi(t)+\xi(t), \tag{4}$$

where $\chi(t)$ represents short-term deviations in salmon prices and $\xi(t)$ the equilibrium price level at time t. Changes in the short-term deviations,

[2] FCR is a common indicator of feed efficiency, defined as the ratio between input of the feed and the weight gain.

$\chi(t)$, represent temporary changes in salmon prices and are assumed to revert to zero following an Ornstein-Uhlenbeck process,

$$d\chi(t) = -\kappa\chi(t)dt + \sigma_\chi dz_\chi(t). \tag{5}$$

Changes in the equilibrium price, $\xi(t)$, represent fundamental changes that are expected to persist and are assumed to follow an arithmetic Brownian motion process

$$d\xi(t) = \mu_\xi dt + \sigma_\xi dz_\xi(t). \tag{6}$$

The Brownian motion increments of $dz_\chi(t)$ and $dz_\xi(t)$ are correlated with $\rho_{\chi\xi}dt = dz_\chi(t)dz_\xi(t)$. Parameter κ is a mean-reversion coefficient describing the rate at which short-term deviations are expected to dissipate, σ_χ represents the short-term volatility, μ_ξ the equilibrium drift rate and σ_ξ the equilibrium volatility.

In the two-factor price model, the short-term deviations, $\chi(t)$, and the equilibrium price level, $\xi(t)$, are unobservable. We use Kalman filtering in order to compute estimates for the short-term deviations and for the equilibrium price based on observations of spot and forward prices.[3] Our resulting state variables and model parameter estimates are presented in Section 4.2. The closed-form solutions for the optimal stopping problem in (3) does not exist. Therefore, we solve (3) numerically by applying a least squares Monte Carlo (LSM) approach [18,30,39].[4]

3.2. Early harvest model

In this section, we extend the problem under consideration in the GSR-model and present the method to quantify the value of flexibility of harvesting while facing the risk of harmful algal bloom arrival.

At time $t = 0$, a harmful algal bloom is reported by a nearby farm. We let the time period from $t = 0$ to $t = T$ represent the maximum duration of the harmful algal bloom and denote the arrival time of harmful algal bloom by t^{HAB}. The presence of harmful algal bloom at the farm is modeled as a binary variable, $\Gamma(t)$. We let $\Gamma(t) = 0$ if there is no harmful algal bloom at the farm at time t. At the time of the harmful algal bloom arrival and for all subsequent times, $t \geq t^{HAB}$, it holds that, and $\Gamma(t) = 1$:

$$\Gamma(t) = \left\{ \begin{array}{ll} 0 & \text{before a harmful algal bloom arrival,} \\ 1 & \text{during and after the harmful algal bloom arrival} \end{array} \right\},$$

while $\Gamma(0) = 0$.

The effect of the harmful algal bloom on the harvesting profit is that, if $\Gamma(t) = 1$, the salmon dies and cannot be sold. In other words, the value of the fish stock immediately goes to zero if the harmful algal bloom arrives at the farm. The farmer now needs to take this risk into account when choosing the optimal harvesting time. If $\Gamma(t) = 0$ indicating the harmful algal bloom did not arrive, the farmer may continue to grow the fish and harvest at the optimal weight and price. In such a case, the optimal harvesting time is given by the GSR-model in Section 3.1.

As previously mentioned, the true risk of receiving a harmful algal bloom is difficult to predict. However, during the harmful algal bloom threat from $t = 0$ to $t = T$, the farmers receive information about algal spread from different sources, e.g. word of mouth from neighboring farms and reports from research organizations. Based on these signals farmers can form beliefs about the true algal arrival rate. Similar to [57], we assume that the signals arrive according to a Poisson process with intensity $\mu > 0$. The signals are either good, representing state where the risk of getting the harmful algal bloom is low, or bad corresponding to the high risk state. The low and high states are denoted by L and H, respectively, and the arrival rates corresponding to these two states are denoted by λ_L and λ_H. The risk of harmful algal bloom arrival in H is higher than in L, i.e., $\lambda_H > \lambda_L \geq 0$. The farmer does not know which risk state the farm is in when the harmful algal bloom is first reported at $t = 0$. However, the salmon farmer has a prior belief about the probability of being in state H: $P(H) = p_0$. Whenever a signal arrives, the farmer updates its belief about the true state. Moreover, the signals are known to be imperfect, and the farmer considers the probability of a signal being correct to be P_{cs}, see Table 1.

We denote the cumulative sums of good and bad signals that have arrived up until time t as l_t and h_t, respectively. In addition, we introduce k_t as the amount of bad signals in excess of good signals that has arrived from time 0 to time t, i.e., $k_t = h_t - l_t$. By following Bayes' rule, the belief that the world is in the high risk state H, can be formulated as a function of k_t.[5]

$$p(k_t) = \frac{P_{cs}^{k_t}}{P_{cs}^{k_t} + \frac{1-p_0}{p_0}(1 - P_{cs})^{k_t}}. \tag{7}$$

At time $t = T$, the harmful algal bloom risk becomes zero and the signals stop arriving. In this case, the optimal harvesting problem is reduced to the GSR-model in Section 3.1.

In addition to actively learning from signals arriving, farmers are passively learning about the salmon price. Thus, farmers have an incentive to wait for more information in order to make better-informed decisions. However, the benefits of waiting for more information about the algal arrival rate and possibly a higher price, must be weighted against the risk of losing the current biomass altogether due to algae arriving. This is a realistic representation of the trade-off faced by salmon farmers in an event of harmful algal bloom.

The optimal stopping problem the farmer faces can now be formulated as

$$F_{EH}(\tau, S_\tau) = \sup_\tau E\left[\left(B(\tau)(S_\tau - C_H)e^{-r\tau} - \int_0^\tau C_p(t)e^{-rt}dt\right) \times (1 - \Gamma(\tau))\right], \tag{8}$$

where τ is the optimal harvesting time. This optimal stopping problem is similar to (3), with the difference that now we take into account the possibility that in the event of the harmful algal bloom arrival the value reduces to zero.

If the farmer endures the harmful algal bloom event without the harmful algal bloom arriving at his location, i.e., $\Gamma(\tau) = 0$ and $\tau \geq T$, it is possible to grow the fish further and harvest at the optimal weight and price. In such a case, (8) is reduced to (3).

Similar to (3), the analytical solution for (8) is not available and we solve the problem numerically using LSM approach.

3.3. Early harvest move model

In this section, we extend the EH-model above by including the option to move the fish. We do so in order to emphasize that in some cases, farmers may have the opportunity to move their fish to another location without harmful algal bloom threat, as an alternative to early harvesting. We denote the extended model the EH-M-model. When moving the fish to another location, the farmer is able to harvest at the optimal time

Table 1
Probability of a signal indicating high or low harmful algal bloom risk, given the true state of the world.

Risk/signal	h	l
H	P_{cs}	$1 - P_{cs}$
L	$1 - P_{cs}$	P_{cs}

[3] The details behind this procedure can be found in the electronic Appendix A.

[4] For more details behind the LSM application to our models see the electronic Appendix B.

[5] See [57].

at the new location, similar to the GSR-model. However, the move may be stressful for the salmon resulting in a higher mortality rate and a higher FCR, which we denote by M_M and f_{rM}, respectively. Furthermore, the move comes at a direct cost of renting a wellboat for fish transportation. We denote the total moving costs per kilogram fish by C_M.

As a result, the option value of moving is the value of harvesting optimally at the new location (without harmful algal bloom risk, but with the higher mortality and FCR), less the moving cost. This option value is compared to the value of waiting and receiving more information about the algal risk. The optimal stopping problem the farmer that considers the options to move the fish and harvest at the optimal time later can be formulated as

$$F_M(\tau_1,\tau_2,S_{\tau_2}) = \sup_{\tau_1,\tau_2,\tau_1<\tau_2} E\Bigg[\Bigg(\Bigg(\sup_{\tau_2} E\Big[B(\tau_2)(S_{\tau_2}-C_H)e^{-r(\tau_2-\tau_1)} - \int_{\tau_1}^{\tau_2} C_p(t)e^{-r(t-\tau_1)}dt|\mathscr{F}_{\tau_1}\Big] - C_M B(\tau_1)\Bigg)e^{-r\tau_1} - \int_0^{\tau_1} C_p(t)e^{-rt}dt\Bigg) \times (1-\Gamma(\tau_1))\Bigg] \quad (9)$$

where τ_1 is the optimal moving time and τ_2 is the optimal harvesting time after moving. The innermost supremum of (9) represents the value of producing at the new location and harvesting optimally at time τ_2, discounted back to the time of moving, τ_1, conditional on information available at τ_1, $\mathscr{F}_{\tau_1}$. Next, we subtract the discounted cost of moving the biomass at time τ_1 and the production costs incurred until τ_1. Lastly, we take into account the probability that the harmful algal bloom reached the farm before moving, represented by $\Gamma(\tau_1)$.

The general optimal stopping problem the farmer faces when choosing between early harvest and moving can be formulated as

$$F_{EHM}(\tau,S_\tau) = \sup_{\tau_1,\tau_2,\tau_1<\tau_2} E[e^{-r\tau_1} max\{F_{EH}(\tau_1,S_{\tau_1}),F_M(\tau_1,\tau_2,S_{\tau_2})\}], \quad (10)$$

where τ is the time when the salmon farmer either moves or harvests the fish, whereas τ_2 is harvesting time after moving. We solve this model numerically by applying LSM approach.

4. Model parametrization

In this section, we quantify and motivate the input values for our models. We present two case studies, for Norway and Chile. Our parameter estimations are based on relevant aquaculture studies from both regions, in addition to input from Norwegian and Chilean industry experts.

4.1. General single rotation model parameters

First, we present the input values for the GSR-model. These are related to production costs, harvesting costs, mortality, weight development and discount rate. The relevant parameters are summarized in Table 2.

The discount rate, r, is set to 6% for the Norwegian case study and 8% for the Chilean. As suggested by Ewald and Taub [27], we choose the values that are consistent with capital asset pricing model estimates based on the industry betas (which are slightly lower than one for salmon companies) and country-specific market risk premiums for Norway and Chile [20,42]. [6]

Table 2
Summary of relevant Norwegian and Chilean input variables for the GSR-model.

Parameter	Symbol	Norwegian case study	Chilean case study
Discount rate	r	6%	8%
Feed conversion ratio	f_r	1.3	1.2
Price per kilogram feed	C_F	12 NOK/kg	12 NOK/kg
Harvesting cost per kilogram fish	C_H	3.9 NOK/kg	4.5 NOK/kg
Mortality rate	M	15%	13%

We set the FCR, f_r to 1.3 for the Norwegian case study based on the average values during the last ten production years reported by Directorate of Fisheries and Iversen et al. [21,34]. In the Chilean case study, the FCR is set to 1.2 to reflect the recent trend of Chilean FCR declining beyond the one in Norway. The feed price, C_F, is set to 12 NOK/kg for both case studies based on the current feed price level and the increasing price trend over time [21,34]. Our harvesting cost estimate, C_H, are based on cost studies undertaken by Directorate of Fisheries [21] and are set to 3.9 NOK/kg for Norway and 4.5 NOK/kg for Chile. We assume 15% higher harvesting costs in Chile because of lower degree of automation at processing plants and lower standard on infrastructure. The mortality rates, M, are set to 15% and 13% for the Norwegian and Chilean case studies, respectively. The former is determined based on the data on fish mortality and losses in production [10,24]. We assume a slightly lower mortality rate for the Chilean case study in line with the estimates of production losses from 2016 and 2017 in Iversen et al. [34].

We assume that the salmon weight function, $W(t)$, follows the deterministic process described in Section 3.1. Similar to [26], we set the parameters of the von Bertalanffy's function in Norway to be a, b, and c to 1.113, 1.097, and 1.430 respectively. We set the asymptotic average weight, w_∞, to be 5.5 kg. Then, the salmon will reach a weight of approximately six kilogram after two years in the sea [56]. As salmon grows slightly faster in Chile due to higher water temperatures [45], we set $b = 1.000$ in Chilean case study.

We let the time since the start of the sea phase, t_{sea}, be either 200, 400 or 600 days, representing the early, middle and late stage of the sea phase, respectively. Given that the maximum allowed biomass (MAB) in Norway is 780 tonnes per licence, we choose the number of recruits, R_0, so that the total biomass reaches the MAB at the end of the sea phase (assumed to be 24 months). Table 3 shows the number of fish in the pen for different values of t_{sea}, including corresponding individual fish weight and total biomass. These estimates will be used in both case studies to make meaningful comparisons.

We set the maximum length of a single rotation sea phase, T^{sp}, to two years, or 730 days, in both case studies. This is done in order to account for the fact that no farmers operate on a single rotation basis, as keeping a single generation of fish for longer than two years is not viable economically.

4.2. Parameter estimation for the two-factor salmon spot price model

In the estimation of the two-factor model, we make use of historical salmon spot prices and forward contracts to estimate the model's unknown parameters (κ, σ_χ, μ_ξ, σ_ξ, $\rho_{\chi\xi}$, $\chi_{t=0}$ and $\xi_{t=0}$). Our data consists of weekly observations of spot prices and forwards from Fish Pool, spanning week 14, 2013 to week 18, 2020. The synthetic FPI spot prices are updated weekly. For the forwards, we let the closing price of the last trading day of a week represent the week's closing price. We include

Table 3
Number of fish in the pen, R_0 for different values of t_{sea}, individual fish weight $W(0)$, and total biomass $B(0)$.

		Norwegian case study		Chilean case study	
t_{sea}	R_0	Weight	Total biomass	Weight	Total biomass
200 days	151,981	1.27 kg	193,372 kg	1.55 kg	236,215 kg
400 days	139,989	3.81 kg	533,707 kg	4.07 kg	569,474 kg
600 days	128,943	5.65 kg	728,205 kg	5.80 kg	747,506 kg

[6] These estimates are also in line with the discount rates used by key players in the industry [16,50].

forwards with maturities ranging from one month up to a year, and with 18 months, two, three, four and five years to maturity. This gives a total of 368 weekly price observations of spot prices and 17 different forward contracts as input for our parameter and state variables estimation. Table 4 presents the parameter estimates from the Kalman filter.

In our model, we disregard the potential effects of size and environmental shocks on salmon prices (see, e.g., [8]), which is an interesting extension of our analysis. Intuitively, adverse effects of harmful algal bloom on prices would increase value of information even more, supporting the conclusions of our model.

4.3. Harmful algal bloom models parameters

In this section we discuss the variables that appear in EH-model and in EH-M-model. These are related to the signal and algal processes and to the consequences of moving the fish. Table 5 below summarizes the relevant input variables.

In the low risk state, we set the algal risk to be zero during a harmful algal bloom: $\lambda_L = 0$. In the high risk state, we set it to $\lambda_H = 0.07$. This implies the expected arrival time of 14.3 days, and the probability of arrival in one day of 6.7%. The probability of the occurrence of harmful algal bloom within the maximum length of 21 days is 77%. The arrival intensity of signals is set to 2 and 1.5 for the Norwegian and Chilean case studies, respectively. This implies on average 2 signals per day in Norway and 1.5 signals in Chile. Table 6 shows the probability of receiving a given amount of signals in one day.

Salmon farmers receive daily signals from various research organizations and policy makers the during harmful algal bloom event. These signals include results from water samples and algal spread simulations. Additionally, most farmers also perform their own sampling and communicate with neighboring farmers about their view of the situation [35]. During the 2019 harmful algal bloom in Norway, however, water samples were conducted and treated differently [35], which negatively affected the reliability of the results from the water samples and simulations. Hence, the probability of a signal being correct, P_{cs}, is set to 75% for Norway and 60% for Chile. In Chile, both the arrival rate of signals and the probability of correct signals are lower than in Norway due to a smaller degree of collaboration among the farmers and governmental organizations compared.

We assume that moving the biomass to an alternative location is conducted through the use of wellboats.[7] In line with Liu et al. [38], we assume that harvesting costs (including the use of wellboat) make up about 12% of the total production costs with wellboats accounting for

Table 4
Parameter estimates for the two-factor price model. The sybmols *** and ** denote significance at 1% and 5% levels, respectively.

Parameter	Description	Estimate	S.E.
κ	Short-term mean-reversion rate	2.692***	0.511
σ_χ	Short-term volatility	0.486***	0.029
μ_ξ	Equilibrium drift rate	0.074**	0.033
σ_ξ	Equilibrium volatility	0.073**	0.033
$\rho_{\chi\xi}$	Correlation in short-term and equilibrium process increments	-0.372***	0.149
$\chi_{t=0}$	Log short-term deviation at time $t = 0$	-0.26 NOK/kg	–
$\xi_{t=0}$	Log equilibrium price level at time $t = 0$	4.18 NOK/kg	–

[7] We assume that reserve facility is already available for the farmer to transfer the fish. This is because in the times of harmful algae outbreak the farmers need to act quick to avoid losing the biomass. Then, the time associated with the set up of a reserve location will prevent the salmon farmer to move the fish on time and the move option becomes irrelevant.

Table 5
Summary of relevant Norwegian and Chilean input variables for the models.

Parameter	Symbol	Norwegian case study	Chilean case study
HAB arrival intensity in state *i*	λ_i	0.07	0.07
Arrival rate of signals	μ	2	1.5
Probability of signal being correct	P_{cs}	0.75	0.60
Moving cost per kilogram fish	C_M	3.0 NOK/kg	2.8 NOK/kg
Feed conversion ratio after moving	f_{rM}	1.50	1.40
Mortality rate after moving	M_M	20%	18%

Table 6
Probabilities of receiving different amount of signals in one day for the two case studies.

Case	μ	0 signals	1 signal	2 signals	3 signals	4 or more signals
Norway	2.0	13.5%	27.1%	27.1%	18.0%	14.3%
Chile	1.5	23.2%	33.5%	25.1%	12.6%	5.6%

4%. Given that the cost of an urgent move during a harmful algal bloom is larger than that of a planned move operation, we set total moving costs, C_M, to be 3 NOK/kg and 2.8 NOK/kg in Norway and in Chile, respectively. The lower values for the Chilean case study are due to cheaper labor costs. The FCR is assumed to increase approximately by 15% after moving the biomass to another facility, as higher fish densities during transportation, loading, and unloading is a source of increased stress levels which can cause higher FCRs [11,15]. Therefore, we set the value of FCR after moving, f_{rM}, to 1.5 and 1.4 for Norway and Chile, respectively. The mortality rate after moving, M_M, is set to 20% and 18% for Norway and Chile, respectively. We assume that the mortality rate after transportation is increased by 5% points, due to potential disease spread as a result of higher densities and stress levels during the move [15].

Lastly, we set the maximum duration of the harmful algal bloom, T, to 21 days, which is equal to the duration of Norwegian harmful algal bloom in 2019 [35].

5. Results and discussion

In this section, we present and discuss results from the Norwegian and Chilean case studies of the GSR-, EH- and EH-M-models. The objective of this section is to identify optimal choices for salmon farmers in Norway and Chile under the various models. In particular, we quantify the added value of flexibility under the GSR-, EH-, and EH-M-models for three different stages of the sea phase and discuss relevant policy insights.

5.1. General single rotation model results

Table 7 presents the GSR-model's option values based on 200,000 price simulations and with a weekly harvesting decision ($\Delta t = 7$). Results are presented for different stages of the production cycle, t_{sea}, representing early, middle, and late stages of the sea phase. We do this for both the Norwegian and the Chilean parameter sets. Planned harvest shows the harvesting value when it must be performed on the last day of the production cycle. The last two columns quantify the additional value of managerial flexibility in the harvesting timing, in comparison to planned harvest.

It is evident from Table 7 that there is significant value in having the flexibility to optimally time the harvesting decision during the production cycle. This holds for all three stages of the sea phase in both Norway and Chile. Note that the value of flexibility is decreasing towards the end of the production cycle when there is less time to take advantage of this

Table 7
The results of GSR-model for the Norwegian and Chilean case studies.

t_{sea}	Case	Planned Harvest	GSR-Model	Value of Flexibility	Percentage increase
200 days	Norway	38.70 MNOK	41.27 MNOK	2.57 MNOK	6.64%
400 days	Norway	42.96 MNOK	44.73 MNOK	1.77 MNOK	4.18%
600 days	Norway	42.38 MNOK	42.65 MNOK	0.26 MNOK	0.61%
200 days	Chile	40.25 MNOK	43.15 MNOK	2.90 MNOK	7.20%
400 days	Chile	43.97 MNOK	45.92 MNOK	1.95 MNOK	4.44%
600 days	Chile	42.81 MNOK	43.07 MNOK	0.26 MNOK	0.61%

flexibility.

Fig. 1 shows the distribution of optimal harvesting time for the Norwegian and Chilean case studies. We see that the majority of the harvests still occur towards the end of the production cycle. We observe that salmon farmers in Chile generally will use the option to harvest earlier than planned more often than Norwegian farmers. This explains the slightly higher values of flexibility for the Chilean case study observed in Table 7.

The Norwegian and Chilean exercise boundaries are represented in Fig. 2 by blue and red curves, respectively. The boundaries separate the two regions where one should harvest (on and above the lines) and where the farmers should continue farming (below the lines). Differences between these boundaries come from the fact that the salmon grows faster earlier in the sea phase in Chile compared to Norway, which makes the value of harvesting higher. At the same time, the value of continuing growing the biomass is lower in the later stages.

The peaks of the curves coincide with peaks of the biomass growth. Shortly thereafter, the exercise boundaries decline quickly, and on the day of expiry (day 530) the salmon is harvested for any spot price. Intuitively, the biomass is only harvested when the spot price is much higher than the equilibrium price early in the production cycle. This trend continues until the biomass growth starts diminishing when the mortality exceeds the salmon weight gain late in the growth cycle. When the biomass growth declines the benefit of growing the salmon further becomes smaller, which means that the exercise region gets more inclusive. In other words, the exercise boundary decreases. This result indicates that under normal production conditions without algal risk, harvesting typically occurs towards the end of the production cycle.

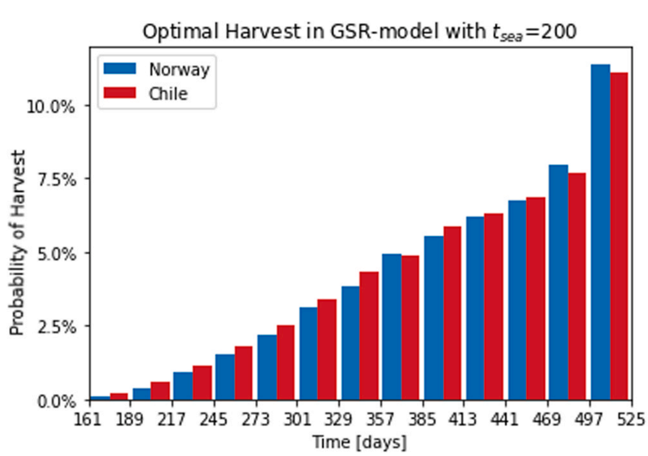


Fig. 1. Probability of optimal harvest time in the GSR-model for Norway and Chile with $t_{sea} = 200$.

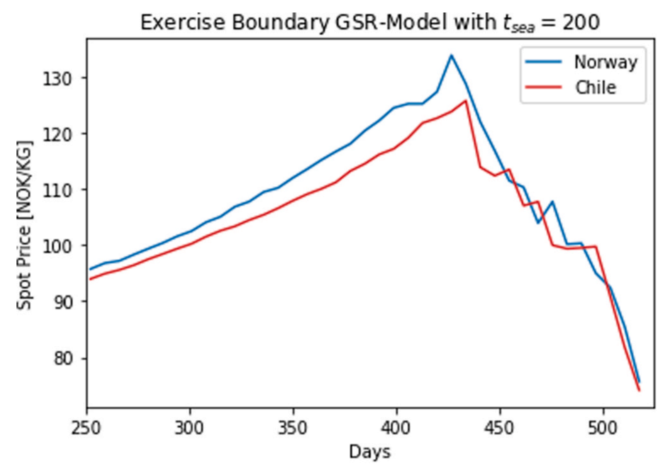


Fig. 2. Exercise boundaries over time in the GSR-model for Norway and Chile cases for $t_{sea} = 200$ and fixed equilibrium price $\xi_t = \ln(65.36)$. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article).

5.2. Early harvest model results

Results from the EH-model are presented in Table 8.[8] Immediate Harvest represents the value of the salmon farmer that decides to harvest immediately after the harmful algal bloom occurs (i.e., on the first day of the harmful algal bloom outbreak). No Early Harvest represents the value if the salmon farmer has no possibility to harvest during the harmful algal bloom. Alternatively, this can be interpreted as the value of the farmer that ignores the signals and accepts the risk of losing the biomass to the harmful algal bloom. The next column, EH-model, is the value of harvesting optimally during and after the harmful algal bloom. Finally, the Value of Early Harvest is the excess value of having the option to harvest during a harmful algal bloom compared to not having any managerial flexibility during the harmful algal bloom, and is calculated by subtracting the value of No Early Harvest from the value of the EH-model. We use the term option value and value of early harvest interchangeably throughout this section.

It is evident from Table 8 that in the EH-model, the value of early harvest is positive for $t_{sea} = 400$ and $t_{sea} = 600$ for both case studies. However, the value of early harvest is zero for $t_{sea} = 200$. This counter-intuitive result can be explained as follows. Early on in the sea phase, the biomass has the biggest potential for further growth. Given that in the high risk state the harmful algal bloom arrival rate is $\lambda_H = 0.07$, there is a 23% chance of surviving the harmful algal bloom.[9] Thus, even if the farmer is perfectly certain that the true risk state is H at the beginning of the harmful algal bloom, there is 23% chance of getting the value of

[8] The results are based on 15,000 simulations of price, signals and harmful algal bloom. Furthermore, the results are obtained with $\Delta t = 1$, meaning that the farmer makes a daily decision during the harmful algal bloom. The compound option values are found by 10,000 simulations each, and $\Delta t = 14$.

[9] $P(\text{No arrival in 21 days}|\text{High state}) = e^{-0.07\times 21} = 0.23$.

Table 8
The results of EH-model for the Norwegian and Chilean case studies.

t_{sea}	Case	Immediate Harvest	No Early Harvest	EH-model	Value of Early Harvest
200 days	Norway	8.91 MNOK	24.99 MNOK	24.99 MNOK	0 MNOK
400 days	Norway	24.74 MNOK	27.33 MNOK	31.24 MNOK	3.91 MNOK
600 days	Norway	33.82 MNOK	25.90 MNOK	35.02 MNOK	9.12 MNOK
200 days	Chile	10.84 MNOK	26.23 MNOK	26.23 MNOK	0 MNOK
400 days	Chile	26.14 MNOK	28.15 MNOK	29.47 MNOK	1.32 MNOK
600 days	Chile	34.31 MNOK	26.22 MNOK	34.31 MNOK	8.09 MNOK

harvesting optimally at a later stage, which amounts to a higher expected value than the value of immediate harvest.[10] This is why early in the sea phase, it more attractive to avoid early harvest. As we show later, if the probability of harmful algal blooms arriving in the state H is increased, early harvest has a positive value in the early sea phase as well.

Fig.s 3 and 4 visualize the distribution of cash flows from Immediate Harvest, No Early Harvest and under the EH-model for the Norwegian and Chilean case studies from Table 8. The blue, red and green bars represent the values of cash flows from immediate harvesting, from ignoring the harmful algal bloom risk and from following the EH-model, respectively.

For $t_{sea} = 200$ in Figs. 3a (Norway) and 4a (Chile), we observe that the optimal choice in the EH-model coincides with No Early Harvest. Consequently, we observe that the value of early harvest is 0 MNOK for $t_{sea} = 200$ in Table 8. For $t_{sea} = 400$ and 600, the probability of losing the biomass to the harmful algal bloom when following the EH-model is reduced compared to doing No Early Harvest. The probability of getting the highest payoff is also slightly reduced. However, the value of the cash flow received as a result of early harvesting outweighs the reduction in probability of getting the highest cash flows. Thus, for the middle and late stages of the production cycle, following the EH-model yields higher values than by ignoring the harmful algal bloom risk. In Fig. 4c for Chile, we observe that the EH-model suggests harvesting immediately at the report of a harmful algal bloom. This occurs as a result of lower signal arrival rate and lower signal reliability, implying that it is more valuable to harvest early in the late stage of the cycle than to risk losing the biomass to harmful algal bloom while waiting for more information.

Table 9 shows the probabilities of different outcomes under the EH-model, including the probabilities of losing the biomass to harmful algal bloom, performing an early harvest, and enduring the harmful algal bloom (i.e., survive the harmful algal bloom event and optimally harvest after the harmful algal bloom period).[11] These are prior probabilities at the time of the first report of harmful algal bloom, i.e., at time t_0 in the EH-Model with no signals received.

Table 9 shows that by following the EH-Model, decision-makers can drastically reduce the probability of losing biomass to harmful algal blooms, creating an added value for risk management actions. For $t_{sea} = 200$, the results are the same for Norway and Chile. For $t_{sea} = 400$, the probability of losing biomass to harmful algal blooms for the Norwegian case study is lower than for the Chilean case study. The Norwegian salmon farmers also conduct early harvesting more often during the harmful algal bloom outbreak for this sea phase stage. This is due to more accurate and frequent information about the potential outbreaks in Norway. Therefore, they are able to make better-informed decisions compared to Chilean farmers. It is evident from Table 9 that there is 0% chance of the losing biomass to harmful algal bloom for the Chilean case study for $t_{sea} = 600$, as the optimal choice is to harvest immediately. This result is again related to the availability of reliable information where the Chilean salmon farmers are worse off.

Fig. 5 illustrates the distribution of early harvests on a given day during the harmful algal bloom duration of three weeks for both case studies when $t_{sea} = 400$.

We see that Norwegian salmon farmers are more likely to perform an early harvest the first days after harmful algal bloom detection compared to Chilean salmon farmers. This is because salmon farmers in Norway receive more reliable signals which serve as a better foundation for decision making. Fig. 5 shows that there is a decreasing probability of performing an early harvest as the number of days increases. Thus, our model suggests that the decisions regarding whether to harvest early should be undertaken in the beginning of the harmful algal bloom.

In Fig. 6a (Norway) and b (Chile), we study how the exercise boundary evolves over time while keeping spot and equilibrium prices fixed. We fix the spot price to the last observed spot price from Fish Pool and the equilibrium price to the estimated equilibrium level from the two-factor price model.

Fig. 6 illustrates the optimal harvesting strategies the first week of a harmful algal bloom outbreak for different stages of the sea phase. For example, in Norway one should perform an early harvest on day four in the middle stage of the production cycle ($t_{sea} = 400$) if k is five or above (given the same spot and equilibrium prices), whereas in Chile this is the case if k is four or above. Note that at the late stage ($t_{sea} = 600$), the exercise boundary for Chile is at $k = 0$ for the first four days. This indicates that it is optimal to harvest immediately in this case. This illustrates how the EH-model may be used to produce optimal harvesting strategies for different scenarios.

5.3. Sensitivity analysis

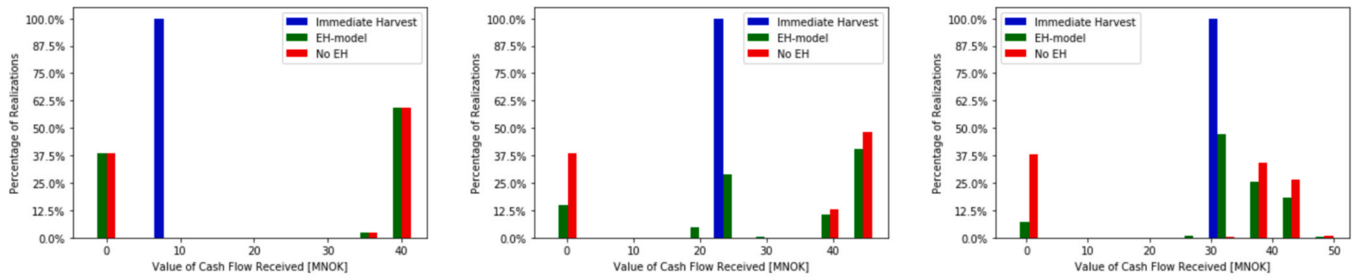
In this section, we summarize the results of the sensitivity analysis with respect to several model parameters.[12] First, we focus on the reliability and frequency of the signals about the potential outbreaks. These parameters are highly relevant for industry organizations and policy-makers as they can directly influence the flow and the quality of information. According to our model, the salmon farmers are not sensitive to changes in the arrival rate of signals for the later stages in the sea phase whereas the early harvest choice is conducted with higher probability as the arrival rate increases. Therefore, it is crucial for salmon farmers to receive signals about the harmful algal bloom risk as early as possible, implying that policy-makers should enhance collaboration between salmon farmers themselves and companies with knowledge related to detecting harmful algal blooms. In addition, centralized reporting of harmful algal bloom events, as well as national or regional monitoring programs should be encouraged to improve harmful algal bloom detection.

Furthermore, we find that the reliability of signals has a great impact on the early harvesting decision. More specifically, higher signal reliability implies that the farmer can make a better-informed decision earlier in the harmful algal bloom event. If the harmful algal bloom event happens during the middle stage of the sea phase, a higher reliability implies more early harvests in the first days. In the late stage of

[10] $0.23 \times 42.27\text{MNOK} = 9.5\text{MNOK} > 8.91\text{MNOK}$.

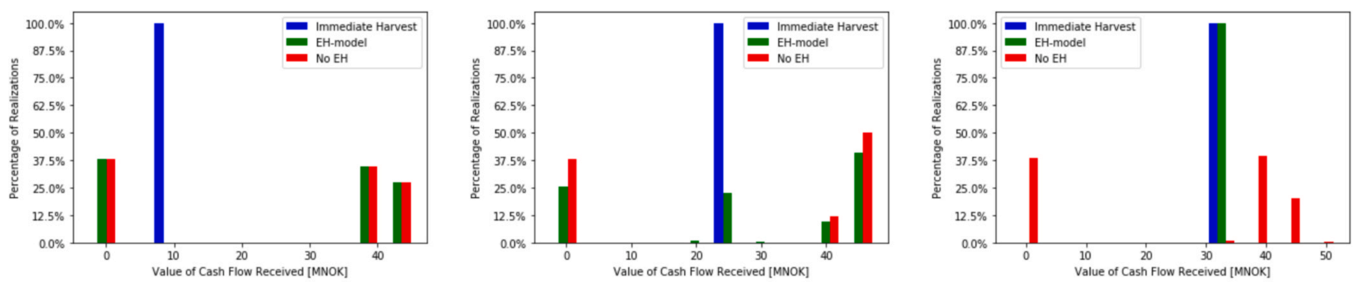
[11] harmful algal blooms are expected to arrive in 38.5% of the realizations in both case studies ($P(H) \times P(HAB|H) = 0.5 \times (1 - e^{-0.07\times 21}) = 38.5\%$).

[12] More detailed results of the sensitivity analysis are available form the authors upon request.



(a) $t_{sea} = 200$ (b) $t_{sea} = 400$ (c) $t_{sea} = 600$

Fig. 3. Histogram showing the distribution of Cash Flows Received for different strategies for the Norwegian case study.



(a) $t_{sea} = 200$ (b) $t_{sea} = 400$ (c) $t_{sea} = 600$

Fig. 4. Histogram showing the distribution of Cash Flows Received for different strategies for the Chilean case study.

Table 9
Probabilities of losing biomass to harmful algal bloom, performing an early harvest, and enduring the harmful algal bloom for the two case studies at different stages of the sea phase.

t_{sea}	Case	Lose to harmful algal bloom	Early Harvest	Endure
200 days	Norway	38.5%	0%	61.5%
400 days	Norway	15.4%	34.0%	50.6%
600 days	Norway	7.9%	48.0%	44.1%
200 days	Chile	38.5%	0%	61.5%
400 days	Chile	24.5%	25.5%	50.0%
600 days	Chile	0%	100%	0%

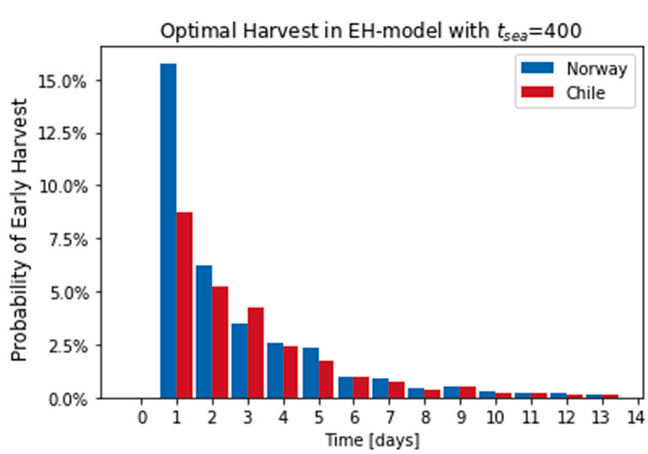


Fig. 5. Probability of early harvests on a given day with $t_{sea} = 400$ for Norway and Chile.

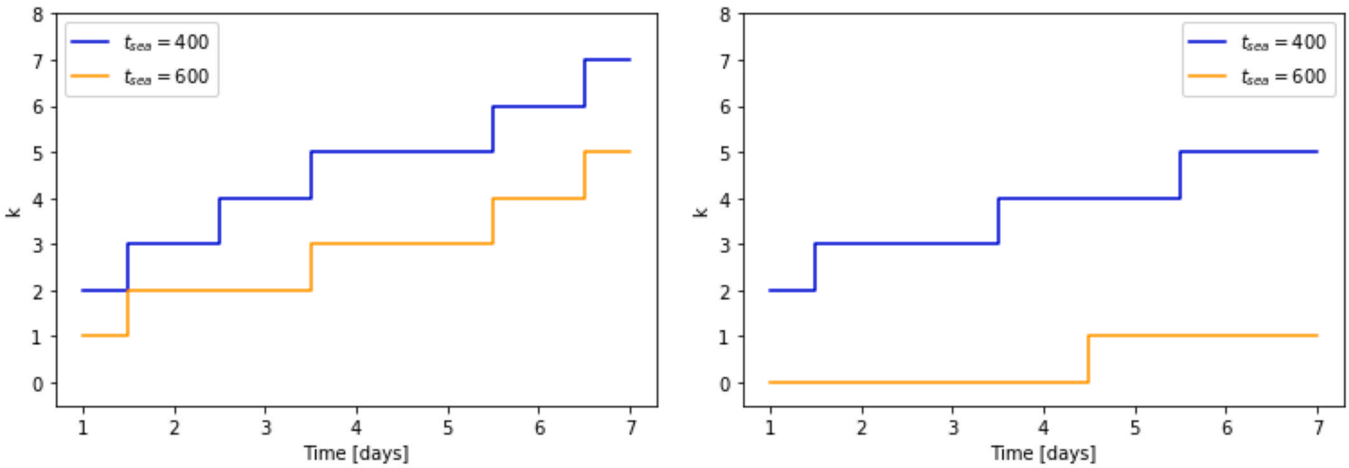
the sea-phase, the opposite occurs. Intuitively, the cost of making a mistake by early harvesting is declining with time. Thus, the model favors restrictive early harvesting in the middle stages of the sea phase and excessive early harvesting in the late stages of the sea phase. Interestingly, our model shows that when the signals are sufficiently reliable, it is worth taking the risk of losing the biomass in order to learn more about the true risk implying that the value of information increases.

Lastly, we discuss the effect of changing the arrival rates in different states due to the high uncertainty surrounding these estimates. We find that the value of the option to harvest early is substantially higher for larger values of harmful algal bloom arrival intensity. As the optimal actions and values of performing early harvests are highly dependent on the actual risk of getting the harmful algal bloom, our results imply that it is essential for policy-makers and aquaculture organizations to contribute to improvements in accuracy and frequency of information signals.

5.4. Early harvest-move model results

Moving the salmon will lead to an increased mortality rate and feed conversion ratio. Consequently, more salmon will die and production costs increase after moving. This obviously leads to a decrease in the value of harvesting optimally at a later stage, if the farmer has moved the biomass compared to endured the harmful algal bloom at the existing location. Still, the possibility to move the salmon is found to be an attractive option with the introduction of harmful algal bloom risk. Table 10 shows the EH-M-model results based on 10,000 simulations of price, harmful algal bloom, and signal processes, with 7,500 compound GSR-model simulations at every time step. Here, the value of harvesting or moving immediately at the report of a harmful algal bloom outbreak is represented by the columns Immediate Harvest and Immediate Move show, respectively. No Move or EH shows the value without the flexibility to move or early harvest. EH-M-model shows the value under the EH-M-model, and Value of Move or EH denotes the added value from the flexibility to choose between moving and early harvesting.

For all stages of the sea phase, the EH-M-model finds it optimal to move immediately at the report of a harmful algal bloom outbreak, hence the values in EH-M-model and Immediate Move columns are equal. This means that it is not worth risking losing the biomass while waiting for signals if the farmer has the option to move. As seen in



(a) Norwegian Case Study (b) Chilean Case Study

Fig. 6. Exercise boundaries for the first week of the harmful algal bloom for Norway and Chile for the spot price of 50.40 NOK/kg and equilibrium price of 65.36 NOK/kg.

Table 10
EH-M-model results presented for different stages of the production cycle for both the Norwegian and Chilean case studies.

t_{sea}	Case	Immediate Harvest	Immediate Move	No Move or EH	EH-M-model	Value of Move or EH
200 days	Norway	8.91 MNOK	35.61 MNOK	24.99 MNOK	35.61 MNOK	10.62 MNOK
400 days	Norway	24.74 MNOK	40.59 MNOK	27.33 MNOK	40.59 MNOK	13.26 MNOK
600 days	Norway	33.82 MNOK	39.55 MNOK	25.90 MNOK	39.55 MNOK	13.65 MNOK
200 days	Chile	10.84 MNOK	36.82 MNOK	26.16 MNOK	36.82 MNOK	10.66 MNOK
400 days	Chile	26.14 MNOK	41.66 MNOK	28.15 MNOK	41.66 MNOK	13.51 MNOK
600 days	Chile	24.41 MNOK	41.01 MNOK	26.22 MNOK	41.01 MNOK	14.79 MNOK

Table 10, the derived value of flexibility to move or early harvest is relatively large. This implies that it is highly beneficial for salmon farmers with alternative farming sites. Furthermore, we find these values to be very similar for Norwegian and Chilean salmon farmers.

These findings imply that salmon farmers should seek to enable spatial diversification if possible. Typically, only the larger salmon farmers have multiple farming sites in different regions and hence the possibility to move their fish during harmful algal blooms. For policy-makers, this has two implications. First, processing of applications for moving the fish during a harmful algal bloom needs to be prioritized to allow for swift moving. Second, decision-makers should look into the possibility to establish a number of reserve fish farming sites in order to support small salmon farmers in the most endangered harmful algal bloom areas. This is of importance to secure workplaces for smaller salmon farming companies and local communities.

The EH-M-model allows for joint consideration of early harvesting and moving, which is especially relevant for larger farmers. Compared to EH-model results in Table 8, we find that the option to move contributes to a significant increase in the value of the salmon farmer (see Table 10). As a consequence, we find that the option to move is dominating both the options to harvest early and to wait in the EH-M-model. Therefore, it is of interest to investigate special cases in which an immediate move is not optimal. Fig. 7 shows the distribution of optimal moves and early harvests in the EH-M-model for different moving costs in the Norwegian case study when $t_{sea} = 600$.

It is evident from Fig. 7 that the option to move dominates the option to harvest early for moving costs substantially higher than our baseline parameter value of at 7 NOK/kg. We observe from Fig. 7 that the percentages of moves and early harvests are equal for a break-even level of moving cost $C_M = 10.68$. Intuitively, the values of the option to move and the option to harvest early evaluated individually should be similar at this moving cost. Fig. 8 shows the values obtained by evaluating the options to move or early harvest individually, as well as the value found by the EH-M-model for different values of moving costs.

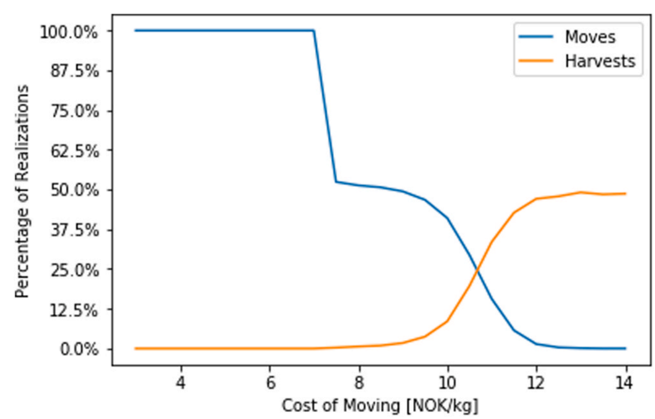


Fig. 7. Plot showing the distribution of early harvests and moves performed during the harmful algal bloom for different values of the moving costs and $t_{sea} = 600$.

Fig. 8 illustrates that when one of the mutually exclusive options is worth a lot more than the other, the value of evaluating them jointly converges to the option with the highest value. However, there is an excess value in evaluating them together. This implies that farmers that have both options should evaluate them jointly in order to maximize the value of their biomass. This is especially relevant in cases where the values of harvesting and moving are relatively similar, such as very late in the sea phase and with high costs of moving.

6. Conclusion

This paper studies optimal harvesting strategies for small and large

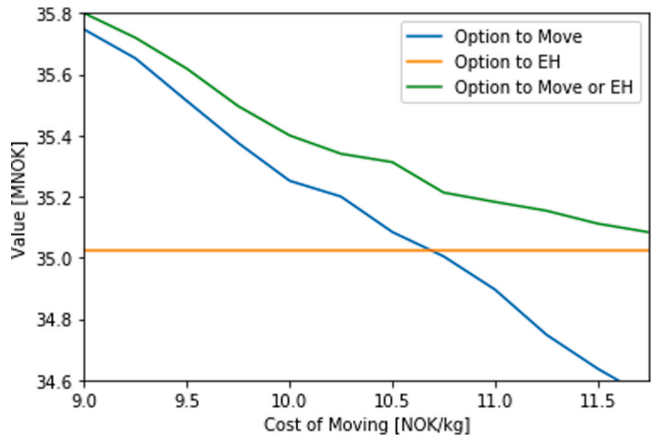


Fig. 8. Plot showing the value of the option to move and early harvest evaluated individually, and as mutually exclusive options found by the EH and EH-M models for different values of the moving costs.

salmon farmers when facing the risk of harmful algal bloom arrival and stochastic prices. More specifically, we focus on optimal harvesting decisions and quantify the value of managerial flexibility to harvest the fish early, while receiving imperfect information about the harmful algal bloom risk. In an extension to this framework, we introduce the opportunity to move the fish and investigate how this affects the optimal course of actions. We present two case studies, for Norway and Chile, where we use realistic model parameters that have been identified from interviews with industry experts and existing literature. Our results are found to be robust to both geographical settings. Furthermore, we provide several recommendations for policy-makers regarding how they can facilitate optimal decision-making for salmon farmers during harmful algal blooms. Our main findings can be summarized as follows.

First, our model uncovers excess value when accounting for managerial flexibility in the harvesting decision. By properly accounting for inherent uncertainties in their decision making process, salmon farmers are able to capitalize on timely information regarding price evolution and harmful algal bloom spread. This value, however, varies across the production cycle. In particular, the harvesting flexibility has little value in the early stages of the sea phase, but becomes more attractive for later stages. As a consequence, if the harmful algal bloom occurs early in the sea phase stage when the biomass is low, our model suggests that salmon farmers should ignore the signals and avoid early harvest. However, if the harmful algal bloom arrival intensity is sufficiently large, we find that the flexibility to harvest early is valuable even for the early sea phase stages.

Second, we find that when the signals regarding the harmful algal bloom spread are sufficiently reliable, it is worth postponing harvesting decisions and, thus, taking the risk of losing the biomass in order to gather more information about the harmful algal bloom risk. Conversely, if the reliability of the signals is relatively low, salmon farmers late in the sea phase should harvest immediately on the report of a nearby harmful algal bloom event. Hence, an increase in the harmful algal bloom signal reliability leads to better-informed decisions and larger values. The frequency of signal arrivals has a similar effect where a larger signal arrival rate increases the values of salmon farmers. The main policy insight here is that in order to facilitate profitability of the salmon farming enterprises, the policy-makers should contribute to improved signal frequency and reliability by boosting regional testing capabilities, enhancing collaboration between salmon farmers and organizations focusing on harmful algal bloom detection, and centralizing the information flow from the different research institutions.

Third, the results from our case studies suggest that moving the fish out of harmful algal bloom risk areas is the most valuable option for salmon farmers with spatial diversification. If moving costs significantly increase in the future, the options of early harvesting and moving need to be considered jointly in order to avoid sub-optimal decisions. From the policy perspective this has the following implications. First, processing of applications for moving the fish during a harmful algal bloom event needs to be prioritized to allow for swift moving of fish. Second, decision-makers should look into the possibility to establish a number of reserve fish farming areas in order to support small salmon farmers in the most endangered harmful algal bloom areas.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.marpol.2021.104528.

References

[1] J. Abolofia, F. Asche, J.E. Wilen, The cost of lice: quantifying the impacts of parasitic sea lice on farmed salmon, Mar. Resour. Econ. (2017) 32.
[2] D.M. Anderson, Approaches to monitoring, control and management of harmful algal blooms (habs), Ocean Coast. Manag. 52 (2009) 342–347.
[3] D.M. Anderson, A.D. Cembella, G.M. Hallegraeff, Progress in understanding harmful algal blooms: paradigm shifts and new technologies for research, monitoring, and management, Annu. Rev. Mar. Sci. 4 (2012) 143–176.
[4] R. Arnason, Optimal feeding schedules and harvesting time in aquaculture, Mar. Resour. Econ. (1992) 07.
[5] F. Asche, T. Bjørndal, The Economics of Salmon Aquaculture, John Wiley and Sons Ltd,, Hoboken, New Jersey, 2011.
[6] F. Asche, B. Misund, A. Oglend, The spot-forward relationship in the atlantic salmon market, Aquac. Econ. Manag. 20 (2016) 222–234.
[7] F. Asche, A. Oglend, The relationship between input-factor and output prices in commodity industries: the case of Norwegian salmon aquaculture, J. Commod. Mark. 1 (2016) 35–47.
[8] F. Asche, A. Oglend, T. SellandKleppe, Price dynamics in biological production processes exposed to environmental shocks, Am. J. Agric. Econ. 99 (2017) 1246–1264.
[9] F. Asche, R. TveterÅs, Modeling production risk with a two-step procedure, J. Agric. Resour. Econ. 24 (1999) 424–439.
[10] BarentsWatch (2020). Fiskedødelighet og tap i produksjonen.⟨https://www.barentswatch.no/havbruk/fiskedodelighet-og-tap-i-produksjonen⟩.[Accessed: May-26–2020].
[11] T. Basrur, R. Longland, R. Wilkinson, Effects of repeated crowding on the stress response and growth performance in atlantic salmon (Salmo salar), Fish. Physiol. Biochem. 36 (2009) 445–450.
[12] T. Bjørndal, Optimal harvesting of farmed fish, Mar. Resour. Econ. 5 (1988) 139–159.
[13] D. Bloznelis, Salmon price volatility: a weight-class-specific multivariate approach, Aquac. Econ. Manag. 20 (2016) 24–53.
[14] O.M. Brakstad, V. Hagspiel, M.N. Lavrutich, D. Matanovic, Optimal investment decisions in lice-fighting technologies: a case study in Norway, Aquaculture 504 (2019) 300–313.
[15] S. Calabrese, T. Nilsen, J. Kolarevic, L. Ebbesson, C. Pedrosa, S. Fivelstad, C. Hosfeld, S. Stefansson, B. Terjesen, H. Takle, C. Martins, H. Sveier, F. Mathisen, A. Imsland, S. Handeland, Stocking density limits for post-smolt Atlantic salmon (Salmo salar L.) with emphasis on production performance and welfare, Aquaculture 468 (2017) 363–370.
[16] Cermaq (2018). Cermaq Annual Report 2018.⟨https://www.cermaq.com/wps/wcm/connect/cermaq/our-company/annual-report/⟩.[Accessed: May-15–2020].
[17] X. Chen, B. Scholtens, The spot-forward relationship in the atlantic salmon market, Rev. Fish. Sci. Aquac. 27 (2019) 142–151.
[18] G. Cortazar, M. Gravet, J. Urzua, The valuation of multidimensional american real options using the LSM simulation method, Comput. Oper. Res. 36 (2008) 113–129.
[19] P.A. Dalby, G.R. Gillerhaugen, V. Hagspiel, T. Leth-Olsen, J.J. Thijssen, Green investment under policy uncertainty and Bayesian learning, Energy 161 (2018) 1262–1281.
[20] Damodaran, A. (2020). Country Risk: Determinants, Measures and Implications - The 2020 Edition. NYU Stern School of Business, Available at SSRN: ⟨https://ssrn.com/abstract=3653512⟩.
[21] Directorate of Fisheries (2019a). Lønnsomhetsundersøkelser for laks og regnbueørret.⟨https://www.fiskeridir.no/Akvakultur/Tall-og-analyse/Statistiske-publikasjoner/Loennsomhetsundersoekelser-for-laks-og-regnbueoerret⟩. [Accessed: Apr-27–2020].
[22] Directorate of Fisheries (2019b). Tall og fakta om algeoppblomstringen i nord.⟨https://www.fiskeridir.no/Akvakultur/Nyheter/2019/0519/Algesituasjonen-i-nord/Tall-og-fakta⟩.[Accessed: June-04–2020].
[23] Directorate of Fisheries (2020a). Algesituasjonen i nord.⟨https://www.fiskeridir.no/Akvakultur/Nyheter/2019/0519/Algesituasjonen-i-nord⟩.[Accessed: May-26–2020].
[24] Directorate of Fisheries (2020b). Svinn i produksjonen fordelt på art og årsak 2005–2020 (Fylke).⟨https://www.fiskeridir.no/Akvakultur/Tall-og-analyse/Biomassestatistikk/Biomassestatistikk-etter-fylke⟩.[Accessed: May-26–2020].

[25] A. Dixit, R. Pindyck. Investment Under Uncertainty, 1 edition.,, Princeton University Press,, 1994.
[26] C.-O. Ewald, R. Ouyang, T.K. Siu, On the market-consistent valuation of fish farms: Using the real option approach and salmon futures, Am. J. Agric. Econ. 99 (2017) 207–224.
[27] Ewald, C.-O. and B. Taub (2020). Real Options, Risk Aversion and Markets: A Corporate Finance Perspective. Available at SSRN: ⟨https://ssrn.com/abstract=3289100⟩.
[28] O.I. Forsberg, Optimal harvesting of farmed Atlantic salmon at two cohort management strategies and different harvest operation restrictions, Aquac. Econ. Manag. 3 (1999) 143–158.
[29] O.I. Forsberg, A.G. Guttormsen, The value of information in salmon farming. Harvesting the right fish at the right time, Aquac. Econ. Manag. 10 (2006) 183–200.
[30] A. Gamba, Real options valuation: a monte carlo approach, SSRN Electron. J. (2003).
[31] V. Hagspiel, J. Hannevik, M. Lavrutich, M. Naustdal, H. Struksnæs, Real options under technological uncertainty: a case study of investment in a post-smolt facility in norway, Mar. Policy 88 (2018) 158–166.
[32] J.M. Harrison, N. Sunar, Investment timing with incomplete information and multiple means of learning, Oper. Res. 63 (2015) 442–457.
[33] P. Hoagland, S. Scatasta, The economic effects of harmful algal blooms, in: Ecology of harmful algae, 391–402, Springer,, 2006.
[34] A. Iversen, F. Asche, Øystein Hermansen, R. Nystøyl, Production cost and competitiveness in major salmon farming countries 2003-2018, Aquaculture 522 (2020), 735089.
[35] Karlsen, K.M., R. Robertsen, and B. Hersoug (2019). Kartlegging av hendelsesforløp og beredskap under giftalgeangrepet våren 2019 - Astafjorden, Ofotfjorden, Vestfjorden og Tysfjorden.Nofima rapportserie.
[36] S.C. Kumbhakar, R. TveterÅs, Risk preferences, production risk and firm heterogeneity, Scand. J. Econ. 105 (2003) 275–293.
[37] J.H. Landsberg, The effects of harmful algal blooms on aquatic organisms, Rev. Fish. Sci. 10 (2002) 113–390.
[38] Y. Liu, T.W. Rosten, K. Henriksen, E.S. Hognes, S. Summerfelt, B. Vinci, Comparative economic performance and carbon footprint of two farming models for producing Atlantic salmon (Salmo salar): land-based closed containment system in freshwater and open net pen in seawater, Aquac. Eng. 71 (2016) 1–12.
[39] F. Longstaff, E. Schwartz, Valuing american options by simulation: a simple least-squares approach, Rev. Financ. Stud. 14 (2001) 113–147.
[40] T. Lorentzen, L.H. Pettersson, How to estimate costs from harmful algal blooms: economic impacts on wild fisheries, aquaculture and commercial tourism SNF Report No. 26/05, Institute for Research in Economics and Business Administration,, 2005.
[41] R. Mcdonald, D. Siegel, The value of waiting to invest, Q. J. Econ. 101 (1986) 707–727.
[42] B. Misund, Common and fundamental risk factors in shareholder returns of norwegian salmon producing companies, J. Commod. Mark. 12 (2018) 19–30 (Seafood: A Global Commodity).
[43] B. Misund, F. Asche, Hedging efficiency of atlantic salmon futures, Aquac. Econ. Manag. 20 (2016) 368–381.
[44] R.M. Montes, X. Rojas, P. Artacho, A. Tello, R.A. Quiñones, Quantifying harmful algal bloom thresholds for farmed salmon in southern Chile, Harmful Algae 77 (2018) 55–65.
[45] Mowi (2019). Salmon farming industry handbook 2019.⟨https://mowi.com/investors/resources/⟩.[Accessed: Apr-15–2020].
[46] O.B. Nilsen, Learning-by-doing or technological leapfrogging: Production frontiers and efficiency measurement in Norwegian salmon aquaculture, Aquac. Econ. Manag. 14 (2010) 97–119.
[47] A. Oglend, R. Tveteras, Spatial diversification in Norwegian aquaculture, Aquac. Econ. Manag. 13 (2009) 94–111.
[48] J. Pettersen, K. Rich, B.B. Jensen, A. Aunsmo, The economic benefits of disease triggered early harvest: a case study of pancreas disease in farmed Atlantic salmon from Norway, Prev. Vet. Med. 121 (2015) 314–324.
[49] K.H. Roll, Moral hazard: the effect of insurance on risk and efficiency, Agric. Econ. 50 (2019) 367–375.
[50] SalMar ASA (2019). SalMar Integrated Annual Report 2019.⟨https://www.salmar.no/en/latest-reports/⟩.[Accessed: May-15–2020].
[51] H.N. Sandvold, Technical inefficiency, cost frontiers and learning-by-doing in Norwegian farming of juvenile salmonids, Aquac. Econ. Manag. 20 (2016) 382–398.
[52] H.N. Sandvold, R. TveterÅs, Innovation and productivity growth in norwegian production of juvenile salmonids, Aquac. Econ. Manag. 18 (2014) 149–168.
[53] P. Schütz, S. Westgaard, Optimal hedging strategies for salmon producers, J. Commod. Mark. 12 (2018) 60–70 (Seafood: A Global Commodity).
[54] E. Schwartz, J.E. Smith, Short-term variations and long-term dynamics in commodity prices, Manag. Sci. 46 (2000) 893–911.
[55] K. Sellner, G. Doucette, G. Kirkpatrick, Harmful algal blooms: Causes, impacts and detection, J. Ind. Microbiol. Biotechnol. 30 (2003) 383–406.
[56] The Norwegian Seafood Federation (2020). Lakseproduksjon: Norsk laks fra fjord til bord.⟨https://laks.no/lakseproduksjon/⟩.[Accessed: May-16–2020].
[57] J.J. Thijssen, K.J. Huisman, P.M. Kort, The effect of information streams on capital budgeting decisions, Eur. J. Oper. Res. 157 (2004) 759–774.
[58] L. Trigeorgis, Real Options: Managerial Flexibility and Strategy in Resource Allocation, MIT Press, 1996.