Eirik Auråen
Dong Zhang

Stochastic modeling of biomass insurance and early harvest risk by using historical simulation and logistic regression

Master's thesis in Industrial Economics and Technology Management
Supervisor: Maria Lavrutich
June 2019

Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Department of Industrial Economics and Technology Management

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Preface

This paper is conducted as part of achieving a Master of Science at the Norwegian University of Science and Technology (NTNU). The degree specialization is in Financial Engineering at the Department of Industrial Economics and Technology Management.

The paper is a original and independent work by Eirik Auråen and Dong Zhang. Our motivation for writing this paper is based on both professional interest and academic curiosity. As Norway's biggest industry after the oil sector, the aquaculture industry is likely to be of vital importance for the Norwegian economy in the years to come. However, its biological challenges are limiting the future growth of the industry. Due to the unique set of risks in the industry, it is challenging to model biomass insurance contracts, which makes it interesting from an academic perspective. We also believe that biomass insurance is a very attractive risk management tool against biological risks, especially for small- to medium-sized companies.

We want to thank our supervisor Associate Professor Maria Lavrutich for stimulating discussions and rewarding council. Further, we would like to thank Senior Advisor Henning Urke and Jørn Pedersen at INAQ AS for providing valuable insights to the salmon farming industry and connecting us with prominent figures within the business.

Eirik Auråen
Dong Zhang

Trondheim, June 10, 2019

Sammendrag

Den norske lakseoppdrettsnæringen står i dag ovenfor betydelige biologiske risikoer som både begrenser den fremtidige veksten i næringen og har potensial til å påvirke enkelt oppdrettere kraftig. Algeoppblomstringen i Norge i 2019 viste hvor sårbare mindre oppdrettere er og hvor avhengig kommunene har blitt av deres tilstedeværelse. Risikostyringsverktøy som teknologi-investering og geografisk diversifisering er hovedsakelig kun oppnåelig for de største oppdretterne i verden. Biomassforsikring er derimot et skalerbart risikostyringsverktøy som gir sikring mot oppdretternes ekstreme nedsiderisiko. Det bør derfor være et svært attraktivt risikostyringsverktøy, spesielt for små og mellomstore oppdrettere. Likevel er biomasseforsikring lite brukt på grunn av kompleksiteten- og mangelen på standardisering- av å tilby produktet. I tillegg finnes det tegn på at det er lite kunnskap om dette risikovertkøyet blant oppdretterne. Denne forskningsartikkelen forsøker å øke bevisstheten om fordelene med biomasseforskring som et risikostyringsverktøy, og fylle mangelen på akademiske studier på hvordan modelere dette forsikringsproduktet. Nærmere bestemt, har vi utviklet en stokastisk prisingsmodell av biomasseforisking basert på en simuleringer av slaktet biomassefordeling. Vi har fokusert på å modellere risikoen for tvunget-slakt utløst av for høye sjølusverdier, påvisning av pankreas sykdom (PD) eller infeksiøs lakseanemi (ILA). Våre resultater tyder på at det er betydelige forskjeller i risikokarakteristikkene mellom tre ulike produksjonsområder i Norge, som i stor grad påvirker forsikringspremiene. I tillegg bekrefter resultatene våres effekten av geografisk diversifisering ved at oppdretterne kan nærmest halvere forsikringspremien ved å samle tre lokasjoner fra forskjellige produksjonsområder i en og samme kontrakt.

Stochastic modeling of biomass insurance and early harvest risk by using historical simulation and logistic regression

Eirik Auråen*, Dong Zhang*

*Department of Industrial Economics and Technology Management,
Norwegian University of Science and Technology, 7491, Trondheim, Norway

June 10, 2019

Abstract

The Norwegian salmon farming industry is currently facing significant biological risks that both limits the future growth of the industry and has the potential to impact individual farmers severely. Algal bloom in Norway in 2019 revealed the smaller farmers' vulnerability to biological shocks, as well as the municipalities dependence of their existence. Risk management tools such as technology investment and spatial diversification are currently mainly obtainable for the biggest farmers in the world. Biomass insurance, on the other hand, is a scalable risk management tool that provides hedge toward the farmers' worst case scenarios (tail risk). Thus, it should be an attractive risk management tool, especially for small- to medium-sized farmers. However, biomass insurance is underutilized due to the complexity-, lack of standardization- and knowledge- of the product. This paper attempts to raise awareness of the benefits of biomass insurance as a risk management tool, and fill the lack of academic studies on how to price it. Specifically, we have developed a stochastic biomass insurance pricing model based on simulations of the harvest biomass distribution. We have focused on modeling the early harvest risk triggered by either sea lice, pancreas disease, or infectious salmon anemia. Our results indicate that substantial differences in the risk characteristics between different regions in Norway lead to considerable differences in the insurance premiums. In addition, our results confirm the effect of spatial diversification by showing that the farmers can halve the premiums by just pooling together three locations into one insurance contract.

Keywords: Aquaculture; Risk management; Biomass insurance; Early harvest risk; Spatial diversification; Sea lice; Pancreas disease; Infectious salmon anemia

1 Introduction

The global demand for protein is increasing; driven by population growth, socio-economic changes, and recognition of the importance of protein with healthy diet (Henchion, Hayes, Mullen, Fenelon, & Tiwari, 2017). The aquatic animals (fish) has great potential to accommodate the need for more protein as they represent a sustainable alternative in terms of low greenhouse gas emission and water usage (Little, Newton, & Beveridge, 2016). Fisheries and aquaculture industry are two ways of harvesting aquatic animals. According to Asche, Roll, and Tveteras (2016) and FAO (2018), the marine fishery resources are currently being overexploited, fisheries have thus limited potential to cover the increasing protein demand. On the other hand, the aquaculture industry has experienced a formidable growth from a production of a few thousand in 1980 to 2.5 million tons in 2014 (Abolofia, Asche, & Wilen, 2017), and it is still the fastest growing food production sector (FAO, 2018). Among the species farmed in the aquaculture, salmon are among the most successful (Abolofia et al., 2017; Asche et al., 2016). Further expansion of the aquaculture industry and salmon farming are needed to cover the increasing demand for protein. It is, however, challenged by spillovers of biological risks to wild salmon populations and adjacent salmon farms. Parasitic sea lice and salmon disease outbreaks such as pancreas disease (PD) and infectious salmon anemia (ISA) are examples of biological risks that are spilling over and affecting fish welfare negatively. Sea lice feed on host mucus, skin, and underlying tissue, which initially causes the host to experience reduced appetite and growth (Costello, 2006). Then the external wounds and stress make hosts more vulnerable to infections and diseases. Even during specific sea lice treatments in salmon farms, salmon experience increased stress, and it often leads to high mortality rates (Hjeltnes, Bang-Jensen, Bornø, Haukaas, & Walde, 2018). PD and ISA are viral diseases which increase the mortality rate and reduce the appetite and growth of the salmon host (Aldrin, Huseby, & Jansen, 2015). In Norway, to prevent these spillovers and uphold fish welfare, the Norwegian Food Safety Authority (NFSA) strictly regulate and supervise farming operations. With sea lice, NFSA has set upper thresholds for the allowed number of sea lice per fish at each location. If the threshold is exceeded, the farmer is obligated to treat or harvest their biomass within two weeks (Heuch et al., 2005). With ISA and PD, the NFSA has the authority to establish control areas around the locations of interest (Norwegian Food Safety Authoriy, 2018a, 2018c). According to the existing regulations implemented by the NFSA (Norwegian Food Safety Authoriy, 2018b, 2018d), the measures combating ISA in the control areas include forced harvest or destruction of all fish where ISA has been detected, or there is a reason to suspect of ISA. The measures combating PD differs depending on the geographical location of the PD outbreak and the severeness of further PD infection. When PD has been detected at one facility, the NFSA can decide on whether to let the biomass continue to grow or impose forced slaughter of the biomass.

In addition to causing biological challenges, sea lice, ISA, and PD also pose financial challenges to the aquaculture industry and salmon farming operations. First, appetite loss reduces the growth of the biomass (Aldrin et al., 2015; Costello, 2006; Damsgård, Sørum, Ugelstad, Eliassen, & Mortensen, 2004; Liu & Bjelland, 2014), leading to either longer production cycles and higher production costs, or lower harvested biomass and lower revenue. Second, treatment results in increased production costs and higher mortality (Hjeltnes et al., 2018; Liu & Bjelland, 2014), which lowers harvested biomass and revenue. Third, in combination with strict regulations, there is a risk of harvesting prematurely, which lowers the revenue significantly. Furthermore, coastal municipalities has become more and more dependent on the existence of their local fish farmers. The fish farmers are both a great contributor to the municipalities' finances through taxes and sponsorships of local projects, and they are employing a large part of the local population both directly and indirectly down the value chain. A severe biological shock has, therefore, a considerable impact not only on the farmer itself but also to the community it operates in. In spring 2019 in Norway, a poisonous algal bloom killed over 13.200 tons at a relatively small geographical area during only one week. Small farmers operating in the area lost nearly all of their stock, and several mayors expressed their concerns for mass layoffs (Knudsen & Hopland, 2019). In order to ensure a sustainable and profitable growth of the industry and municipalities, it is crucial for the salmon farming companies to know how to mitigate the biological risks optimally.

The available risk management tools for fish farmers to cope with the biological risks can be divided into three main categories: (1) Spatial diversification, (2) technology investment, and (3) biomass insurance. Fish farmers can hedge against biological risks by spatially diversifying their operation by setting up production sites at different geographical locations with less than unit correlations in shock occurrences. By spatially diversify the production, supply and expected returns can be smoothed overtime (Oglend & Tveteras, 2009). Spatial diversification can be obtained by setting up different production locations in the same country. However, there needs to be sufficient distance between them due to the water currents ability to spread diseases and parasites. Besides its ability to reduce the biological risk, spatial diversification also reduces the political risk to the company. Aquaculture is a highly regulated industry, and new legislation both on a national and local level can have a severe impact on the fish farmer. However, to spatially diversify requires farmers to either set up new production sites or consolidate with other farmers and need, hence, substantial capital investments. It will not always be an available risk management tool for small- to medium-sized farmers.

Next, investing in new disruptive technology which has the potential to improve the fish farming operation can be seen as a natural hedge against companies' biological risk. Besides reducing the likelihood of being affected by a biological shock, this tool also has the benefit of reducing the long run average mortality rate to the company. For example, investing in land-based farming can achieve the above two benefits by giving the farmer the ability to control more factors that influence the production. Technology investment also has the potential to reduce biological risks for the industry as a whole, and the government has, therefore, made incentive schemes for taking on such investments (Brakstad, Hagspiel, Lavrutich, & Matanovic, 2019). However, similar to spatial diversification, technology investment requires substantial capital investments and is, therefore, not always an obtainable risk management tool for small- to medium-sized companies.

Finally, the fish farmers can directly cope with their biological risks by transferring them to other parties through biomass insurance. With biomass insurance, the farmer will receive an insurance payout if their realized harvested biomass is significantly lower than the expected amount. First and foremost, this is an insurance against the tail risk that the farmers are facing, such as biological shocks that forces early harvest or spikes in the mortality. It will, therefore, not cover the day to day expected mortality or the uncertainty in weight development that is a natural part of the industry. In contrast to spatial diversification and technology investment, biomass insurance is a scalable product that should be an obtainable risk management tool for all fish farmers. In addition, biomass insurance is the only one of the three risk management tools that gives a total financial hedge against the tail risk. Due to its scalability and directly hedge against such biological shocks, biomass insurance should be especially attractive for small- to medium-sized farmers.

We have briefly investigated how the fish farmers which are listed on the Oslo Stock Exchange are managing their biological risks. Oslo Stock Exchange consists of eight fish farmers from four different countries and represents about 38% of the global salmon farming industry. The main findings from the investigation are shown in Table 1. From this table, we see that the four biggest companies are represented in several regions[1] and, therefore, obtains spatial diversification effects. On the other side, three out of the four smallest companies are represented in only one region, and from Figure 1.1, we see that some of these regions are relatively small.

Company	Harvested biomass in 2017 (kilo tons)	Spatial diversification Number of countries with operational presence	Technology investment				Biomass insurance
			Preventive	Continues	Immediate	Permanent	
Mowi	370	6	Genetics breeding	No info	No info	Post-smolt, CSCS, offshore	No info
Salmar	154	3	Lice skirts, genetics breeding	Cleaning fish	No info	Offshore	No info
Lerøy	135	2	No info	Cleaning fish	No info	Post-smolt	No info
Grieg Seafood	62	3	No info	No info	No info	Post-smolt	No info
Bakkafrost	55	1	No info	Cleaning fish	Freshwater bath	Post-smolt	No info
Chamanchaca	34	1	Genetics breeding	No info	No info	No info	No info
Norway Royal Salmon	32	2	Sterile salmon	No info	No info	Offshore	No info
Scottish Salmon Company	25	1	No info	Cleaning fish	Freshwater bath, hydrolicer	No info	No info

Table 1: Overview of biological risk management practices.

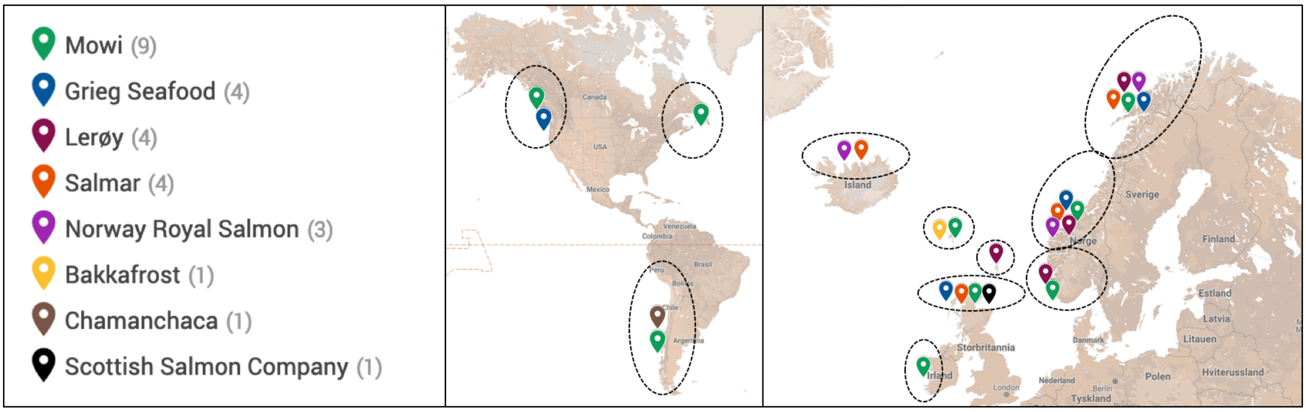


Figure 1.1: Overview of production sites.

Based on these observations, it is reasonable to assume that it is mainly the biggest companies that fully utilize spatial diversification of their operations. Next, Table 1 shows that all of the companies are investing in technologies. As of today, mainly permanent technologies can be categorized as disruptive (Brakstad et al., 2019). Even though most of the companies are investing in them, we see that two out of the three smallest companies are not. Thus, it is again reasonable to assume that it is mainly the biggest companies that fully utilize technology investments as a risk management tool. In addition, this brief investigation is conducted on some of the largest fish farmers in the world, and the trend is likely to be even more prominent among smaller fish farmers that are not listed on Oslo Stock Exchange. Finally, none of the companies mention the use of biomass insurance which indicates an underutilization of this risk management tool.

The above results coincide with the findings made by Bergfjord (2009) in his study on aquaculture farmers' risk perception and risk management practices. Very few of the respondents in his questionnaire reported that biomass insurance were an important risk management tool. He argues that as firms grow larger and become more internationally diversified, self-insurance through spatial diversification become more attractive as opposed to regular insurance services. However, Secretan, van Anrooy, Lou, Roberts, and Upare (2006) find in their review of the aquaculture insurance industry that there is a growing demand for biomass insurance, but a decreasing share of farmers using it. Looking worldwide, Food and Agriculture Organization of

[1]These regions are defined based on the companies annual reports of 2017.

the United Nations (FAO) estimates that in Asia, which is the largest producer of aquaculture products in the world when including all aquaculture species, only about 0.05% of aquaculture farmers used biomass insurance in 2007. According to Secretan et al. (2007), the underutilization could be explained by a lack of knowledge among the farmers in the product and its premium. The perception is that the insurance is too expensive, yet many insurance underwriters would argue that the protection is too cheap based on their experience with losses. Historically, providing biomass insurance has proved to be a challenging task. The aquaculture industry has a track record of generating significant losses on a reasonably consistent basis, and most of the insurance companies have not succeeded in providing an insurance product that generates enough profits to generate the stability needed for the market to expand (Secretan et al., 2007). One aspect of the industry that the insurance companies have recognized as especially challenging when providing such products is the constant and rapid change in how the farms operate, their surroundings, and the people running it (Secretan, 2008). These changes have a direct impact on the risk profile of the farmers. The aquaculture industry belongs to a small insurance class where there are few standards in use, and virtually every growing system is unique (Secretan et al., 2007). Also, the fact that the production is carried out in the water makes it difficult to have precise stock control, spot diseases, and monitoring water pollution.

The insurance marked for the aquaculture industry has existed for over 30 years (Secretan, 2008). However, there seems to be a lack of academic studies on how to model biomass insurance. As mentioned above, biomass insurance is first and foremost an insurance against the tail risk that the farmers are facing, such as early harvest risk and sudden spikes in mortality. Pettersen, Rich, Jensen, and Aunsmo (2015) are among very few that have studied the early harvest risk; however, they only focus on sea lice triggered early harvest and regards it as an optional decision by the salmon farmer rather than enforced by authority despite it often happens in reality.

The contributions of this paper can be summarized as follows: First, as one of the first academic attempts, if not the first, we develop a stochastic biomass insurance pricing (BIP) model that takes into account the early harvest risk. The early harvest risk is modeled as a non-optional decision that can be triggered by either sea lice, PD, or ISA. There exist several studies on how to model sea lice development through explicit mathematical models. However, they struggle to provide precise results. In contrast to these studies, we use a model-free approach through historical simulation to simulate the sea lice development. PD and ISA are modeled with logistic regression. Second, in light of the lack of risk management tools available to small- and medium-sized farmers, this paper contributes to raising the awareness and knowledge of biomass insurance as a risk management tool. In addition, this paper counteracts to the lack of standardization of biomass insurance that has been pointed out as a limiting factor in its utilization. Third, we have conducted an empirical analysis of the sea lice-, PD-, ISA-, mortality- and weight-development and based on this analysis, estimated the BIP-model parameters for three production areas in Norway: production area 3 (P3), 6 (P6) and 9 (P9). In the empirical analysis, we find regime shifts in the change of sea lice level based on the sea lice level itself, and regime shifts in the mortality rates based on production time. Also, the results confirm latitude as an explanatory variable for ISA occurrences which Lyngstad, Qviller, Sindre, Brun, and Kristoffersen (2018) have found in their study. Furthermore, we have calculated the biomass insurance premiums for each of the three production areas. In the case of strict enforcement of regulations, the results reveal substantial regional differences in the premiums. We also compare having one individual contract for each of the production area to a multiple location contract that covers the sum of the biomass from each area in one contract. The result of this comparison is a considerable decrease in the insurance premium, which illustrates the benefit of spatial diversification and how it also can be exploited in an biomass insurance. Our results also indicate that the authorities are not strictly enforcing the current sea lice -, PD-, or ISA-policy. Our sensitivity analysis of the PD-policy regime indicates that there exist a considerable political-risk in P3 and P6 which will push up the premiums in these areas.

The remainder of this paper is organized as follows. Section 2 gives an overview of the relevant literature. Section 3 presents BIP-model based on the findings from Section 2. In Section 4 we present our empirical study of the sea lice-, PD-, ISA-, mortality- and weight-dynamics in P3, P6 and P9. The parameter estimation of the BIP-model is presented in Section 5. Next, the results and sensitivity analyses are given in Section 6. Finally, Section 7 concludes the paper and discusses suggestions for further research.

2 Literature review

Literature on pricing biomass insurance contracts is rather scarce. Contributions that specifically focus on aquaculture insurance and industry are mostly qualitative and descriptive (Secretan, 2008; Secretan et al., 2007), and lacks studies on quantitative methods and mathematical models. On the other hand, there is a large body of research on pricing crop insurance contracts in the agricultural sector which shares several common characteristics with aquaculture sector. Crop in agriculture can be seen as an equivalent to salmon biomass for the following reasons. First, crop and salmon biomass are biological products, and second, they are exposed to volatile and unpredictable biological risks such as parasites, disease, and pests (Flaten, Lien, & Tveteras, 2008). In this paper, therefore, due to the similarities between the underlying assets of both insurance contracts, we take inspiration from crop yield insurance pricing methods in our BIP-model. One method is the net present value method which prices insurance contracts by discounting the expected payout of the contract given a distribution of the underlying asset (Myers, Liu, & D. Hanson, 2005). Another method is the option pricing model which regards the insurance contract as an European put option contract (Myers et al., 2005). According to Sherrick, Zanini, Schnitkey, and Irwin (2004), there is a considerable disagreement about the most appropriate characterization of crop yield distribution. Due to the similarities between crop yield and salmon biomass, it is reasonable to argue that the same apply to distribution of salmon biomass. This results in option pricing method suffers limitations such as the strict assumption about the asset following a log-normal distribution. Therefore, we use the net present value method for in our BIP-model. It is the most commonly used method for valuing insurance contracts, where the most significant advantage of this method is its flexibility. It is straightforward to apply the method and solve it regardless of the underlying asset follows a parametric distribution or a more advanced distribution model generated by simulations. Due to the above mentioned disagreement surrounding distribution for biomass, in this paper, we use a distribution model of salmon biomass through simulations instead of a parametric approach.

Salmon biomass in a pen can be modeled as a product of the number and the average weight of salmon fish. This formulation has been applied in many settings, e.g., to finding optimal feeding of farmed fish (Arnason, 1992; Heaps, 1993), finding optimal rotation (Guttormsen, 2008) and investigating salmon prices and fish farm values (Ewald, Nawar, Ouyang, & Siu, 2016; Ewald, Ouyang, & Siu, 2016). The mortality rate governs the number of fish. Among the early attempts to model salmon biomass, mortality has been considered to be a constant which is set to equal the natural mortality rate of salmon fish Arnason (1992); Heaps (1993). The drawback of constant mortality is an inadequate description of the volatile and unpredictable biological risks which affect the survival of salmon. Stochastic modelling of salmon mortality has been done in recent studies, for example Ewald, Nawar, et al. (2016) applies adapted stochastic process to describe dynamics of salmon mortality rates. Similar to Ewald, Nawar, et al. (2016), in this paper, we apply a stochastic process to govern the behavior of salmon mortality. Several contributions have also explored how to model the average weight of a fish. Among the deterministic models we find Iwama and Tautz (1981) which explains the average weight as a linear function of time. This approach has been used by Thodesen, Grisdale-Helland, Helland, and Gjerde (1999) to investigate whether selection for increased growth rate in Atlantic salmon is connected to increased feed intake and/or better feed utilization. The von Bertalanffy's (VB) growth function is another deterministic average weight model. This model has been widely applied in the aquaculture literature, for example by Ewald, Ouyang, and Siu (2016) for valuing fish farms. It is considered to be the most acknowledged and used model to describe the growth of fish weight (Russo et al., 2009). Lv and Pitchford (2007) has further developed VB - growth function by including a stochastic Brownian motion term. They evaluated how a stochastic term as a function of the larval size influenced the mean growth rate and recruitment[2] probability, and revealed that adding the stochastic term made the model more realistic from a biological standpoint. Our paper focuses on pricing of biomass insurance which is an insurance against the farmers tail risk. The farmers tail risk are mainly explained by the early harvest risk and mortality spikes. Fluctuations in the salmon weight is regarded as part of the day-to-day business in the aquaculture industry and not a part of the tail risk. Modeling the uncertainty in weight development by including a stochastic term increases the computational complexity, however, it will likely have an insignificant effect on the premium. We, therefore, choose to use the widely applied deterministic VB growth function to model the weight development in our BIP-model.

As mentioned earlier, the strict governmental regulations on biological risks can trigger premature harvest of salmon biomass. This element has been neglected in numerous studies that consider harvesting decisions, e.g. by Bjørndal (1988); Ewald, Ouyang, and Siu (2016); Guttormsen (2008). Among the few contributions that take it into account is Pettersen et al. (2015) which investigates the economic benefits of disease triggered early harvest. However, Pettersen et al. (2015) regards early harvests as an optional decision by the salmon farmer enforced by authority despite it often happens in reality. In this paper, we address this by including the regulatory risk of early harvest in the biomass model when deciding how long the salmon can be farmed. This allows us to obtain a more realistic salmon biomass distribution which is used for valuing biomass insurance contracts. Amount of adult female sea lice per fish and detection of PD and ISA are the key factors for the authority to determine the need for early harvest enforcement. Based on the studies of salmon viral diseases, logistic regression analysis has been commonly applied to model PD, and ISA outbreaks. Examples of recent contributions are Kristoffersen, Viljugrein, Kongtorp, Brun, and Jansen (2009); Stene, Viljugrein, Yndestad, Tavornpanich, and Skjerve (2014); Viljugrein, Staalstrøm, Molvær, Urke, and Jansen (2009) on PD, and Lyngstad et al. (2018); McClure, Hammell, and Dohoo (2005) on ISA. Models by Stene et al. (2014); Viljugrein et al. (2009) take into account the hydrodynamics of currents in the fjord which makes the model more realistic, however, it also increases the model complexity and need for extensive data material, and forces the case area to be very small which leads to results that are very location specific. Therefore, in this paper we use the approach of Kristoffersen et al. (2009) and Lyngstad et al. (2018) when studying PD and ISA respectively. Their approach are very similar and do not limit the size of the area under study, in addition they are flexible enough to be used in different regions.

Several studies on the modeling of sea lice development have been done, for instance Rittenhouse, Revie, and Hurford (2016) presents a model which suggest that sea lice growth is correlated with the sea temperature. The model did not take into account sea lice treatment, which in turn resulted in the model failed to explain the sea lice development in part of the data. According

[2]Recruitment refers to a larval fish surviving to reach metamorphosis into adulthood

to Costello (2006); Revie, Robbins, Gettinby, Kelly, and Treasurer (2005), sea lice treatment heavily affects the sea lice level and therefore it should be included in a sea lice model in order to provide accurate description of sea lice development in farming operations. Despite the inclusion of sea lice treatment in the model by Revie et al. (2005), the model is unfortunately inadequate of providing precise estimates of weekly sea lice levels. As different models have not proved to be particularly efficient in describing sea lice development, we apply a model-free approach to simulate sea lice level in a production cycle. We choose historical simulation, due to its advantages of letting the past historical sea lice data to directly tell us about the dynamics of sea lice at a particular area, including how sea lice treatment affects sea lice levels. An underlying assumption with historical simulation is that what has happened in the past will also happen in the future.

As mentioned in Section 1, the perception among the farmers is that the premiums for biomass insurance are too high (Secretan et al., 2007). According to Goodwin and Mahul (2004), there are several ways of adjusting insurance contracts in order to lower the crop yield premium. One is to increase the insurance deductibles. This would lower the probability of triggering and the magnitude of an insurance payout, and, thus, lower the premium. Intuitively, this should also be possible for biomass insurance. Another method to lower premium is to write an insurance contract over multiple locations. Given that the locations are not perfectly correlated, this should lower the premium due to spatial diversification effects. This method is more advantageous as farmers do not need to increase insurance deductibles.As there are small- to medium-sized farmers that operate at more than one location, multiple location insurance contract should be extra attractive for them. In order to investigate possibilities of lowering the insurance premium, we also develop a multiple location biomass insurance model to analyze the effects of pooling together multiple locations and the sensitivity of insurance premiums to the deductibles.

3 Insurance model

In this section, we first combine the findings from existing literature presented in Section 2 and propose a stochastic insurance model which can be used to price biomass insurance in aquaculture. As mentioned in Section 1, the perception among farmers is that the insurance premium is too expensive (Secretan et al., 2007). One way to reduce the premium is to include multiple locations in one contract (Goodwin & Mahul, 2004). Thus, we further develop the model to include multiple locations in one contract in Section 3.2.

3.1 Single location

The model for a single location consists of two main parts. First, a stochastic biomass model that simulates the development of the biomass in terms of total weight. Second, in order to model the tail risk, the farmers are facing, an early harvest mechanism is included. This mechanism determines the length of the production cycle in each simulation. The result of the simulations is a harvest distribution, and we use a NPV method with this distribution to price the biomass insurance contract.

The total weight of the biomass in a sea pen at each given time is a function of the number of fish in the sea pen and the average weight per fish:

$$y_t = n_t w_t, \tag{1}$$

where y_t, n_t and w_t is the total biomass weight, number of fish in the sea pen and the average weight per fish at time t respectively. As mentioned in Section 2, the salmon biomass formulation above has been applied in numerous studies (Arnason, 1992; Ewald, Nawar, et al., 2016; Ewald, Ouyang, & Siu, 2016; Guttormsen, 2008; Heaps, 1993). The number of fish in the sea pen at time t, n_t, is equal to the number of fish in the previous period corrected for the mortality:

$$n_t = n_{t-1}(1 - m_t), \tag{2}$$

where m_t denotes mortality rate at time t. To capture the uncertain nature of the farming operations, m_t is assumed to be stochastic and is modeled using historical simulation. The average weight of the fish in the sea pen, w_t, is determined by VB growth function:

$$w_t = w_\infty(a - be^{-ct})^3, \tag{3}$$

where w_∞ describes the fish's saturation or maximum weight, and c is a curvature parameter which determines how fast the weight approaches the saturation weight w_∞ (Sparre & Venema, 1998). This model is the deterministic VB which has been applied in the study by Ewald, Ouyang, and Siu (2016).

Next, the early harvest mechanism in this paper is based on three factors which the NFSA monitors closely and can use to demand early harvest. These factors are the amount of adult female sea lice per fish and detection of PD or ISA. As mentioned in Section 2, when it comes to describing the occurrence of PD and ISA, logistic regression models have been frequently applied. In our BIP-model, therefore, we use logistic models to determine the probability of PD and ISA occurrence at each given time in the simulated production cycles. They are constructed with a similar approach as in Kristoffersen et al. (2009) and Lyngstad et al. (2018). The estimation of the variable parameters in logistic models is presented in Section 4. In contrast to PD and ISA, the farmers can monitor and influence the sea lice level through sea lice treatments. The sea lice level can, therefore, be viewed as a control variable, and the sea lice level itself likely affects the sea lice dynamics. In order to model the development of the sea lice level, we are using historical simulation based on the sea lice level itself. This approach allows our model to capture the same treatment strategies which have been used historically by the farmers. In Section 4 we investigate which sea lice level intervals that are most appropriate to use in the simulations. Based on these models for PD, ISA and sea lice level, the early harvest mechanism is triggered as soon as either the sea lice level is breached at three consecutive production weeks[3], or immediately at detection of PD or ISA.

The result of these simulations is a harvest distribution, which is used to calculate the biomass insurance premium with a NPV method. The NPV method has been presented by Myers et al. (2005) and calculates the expected payout of the contract and then setting the premium equal to the present value of the payout plus a margin to cover profit, administration- and operational costs. Our biomass insurance contract has the following payout function:

$$G_y = max(0, P \cdot (Y_g - y)), \tag{4}$$

where Y_g is the insured biomass level, y is the realized harvested biomass, and P are the agreed upon price per kg ($/kg). The insured biomass level is calculated as, $\bar{y} \cdot h$, where $\bar{y}$ is the proven yield, and h is an insurance fraction between 0 and 1. The proven yield represents the expected

[3]This has been determined based on conversations with the NFSA. Since sea lice levels can suddenly jump, they usually give the farmers two weeks to reduce the sea lice level again before they force them to harvest.

harvest based on historical data. The insurance fraction, h, determines the deductibles. For example, with a insurance fraction equal to 0.75, the deductibles becomes 0.25 of the proven yield $\bar{y}$. The payout function states that the insurance company compensates the insuree only when the biomass upon harvest is below the insured level, which is a fraction of what the insuree harvests on average. The size of the payout depends on the difference between the harvested biomass and the insured level and on the unit price that has been set upon the signing of the contract. The contract premium can be calculated as follows:

$$P_{Premium}(Y_g) = (1+\gamma)^t \frac{1}{(1+r_f)^t} \int_0^{Y_g} P(Y_g - y) f(y)\, dy, \tag{5}$$

where r_f is the risk-free interest rate which discounts the cash flow from the expected payout, P is the agreed upon price per kg fish, $f(y)$ is the simulated harvest distribution, and γ is a loading factor that compensates the insurers for taking on any non-diversifiable risk plus the administration- and operational- costs of providing the insurance.

3.2 Multiple locations

The model for multiple locations builds further on the model in Section 3.1 by relaxing the assumption of only having one location. The contract for multiple locations insures the sum of realized biomass from multiple locations. The payout function for such a contract can be written as:

$$G_y = max(0, P \cdot (W_g - w)), \tag{6}$$

where W_g is the sum of guarantee levels at each location l, and w is the sum of realized biomass levels at each location l:

$$W_g = \sum_l Y_{g,l}. \tag{7}$$

$$W_g = \sum_l Y_{g,l}. \tag{8}$$

Then, the insurance premium for an insurance contract over multiple locations that are not correlated can be written as:

$$P_{Premium}(W_g) = (1+\gamma)^t \frac{1}{(1+r_f)^t} \int_0^{W_g} P(W_g - w) f(w)\, dw. \tag{9}$$

This contract will be simulated in the same manner as described in Section 3.1. To test the magnitude of such a diversification in the insurance contract, one can calculate the difference between having one contract per location and having one contract for all of them:

$$\Delta Premium = P_{Premium}(W_g) - \sum_l P_{Premium}(Y_g). \tag{10}$$

where $P_{Premium}(W_g)$ is the insurance premium for multiple locations calculated using Equation 9.

4 Empirical study

The BIP model from Section 3 contains two main factors that affect the premium: early harvest risk and the uncertainty in mortality rate. In this section, we first describe our available data materials and its characteristics. Then, we conduct empirical analysis of the two above factors as well as the weight development using descriptive statistics and hypothesis testing. Based on these findings we decide how to best incorporate the dynamics of these factors in our proposed model.

4.1 Description of data materials

Estimation of our proposed model and empirical analysis of early harvest risk, mortality rate and weight development require both production data and disease data. Also, in order to analyze spatial diversification effects of having an insurance contract over multiple locations, data from multiple uncorrelated regions are need. Every fish farmer in Norway is obligated to send their production data to the Norwegian Directorate of Fisheries (NDF). This is defined as sensitive data and is, therefore, not available to the public. However, we managed to get access to the production data from three production areas from 2011 to 2018: P3, P6 and P9. Characteristics related to these areas are described in more detail in Section 4.2, in short, they are geographically distant from each other. And based on the following studies, salmon production in these three areas are regarded as uncorrelated. First, according to Ådlandsvik (2015) 95% of the sea lice stay within its production area. Second, risk of being infected by infectious PD or ISA decrease with increasing distance (Aldrin, Storvik, Frigessi, Viljugrein, & Jansen, 2010). Third, mortality rate is heavily affected by sea lice treatment (Liu & Bjelland, 2014) and weight development by feeding regimes (Damsgård et al., 2004) where both treatment and feeding regimes are company specific and not correlated between companies across production areas. The data from P3, P6 and P9 are thus sufficiently uncorrelated to analyze spatial diversification effects of having an insurance contract over multiple locations. The corresponding disease data for the three production areas are available to the public and can be accessed through *www.barentswatch.no*.

Prior using the data, the data sets have been unified and cleaned for irregularities with simple coding in Microsoft Excel. First, we have excluded incomplete production cycles: Production cycles that either started before or finished after the data sample period has been removed. Then, we have excluded temporarily holdings data, i.e. data that has production cycle time less than 6 months are most likely temporarily holdings and not true production cycles (Kristoffersen et al., 2009). Likewise, production cycles that start with unusually high average fish weights originate most likely from a temporarily holding on another production plant. We have, therefore, also removed production cycles that started with more than an average weight per fish on 300 grams. Those farmers that use post-smolt technologies might have some production cycles where their initial fish in the pen has an average weight above 300 grams. Therefore, we could have excluded some true cycles, however, for our purposes, ensuring that the data set only consists of complete production cycles outweighs the risk of excluding some true data especially when the amount of data is rich. Table 2 gives an overview of the unique number of cycles, production data points and disease data points for each production area after cleaning the data.

Production areas	Number of cycles	Number of production data points	Number of disease data points
P3	229	4269	15040
P6	118	2363	9361
P9	46	917	3156

Table 2: Overview of the unique data points after cleaning the dataset.

In total the production data contains 393 complete production cycles, over 7000 monthly production data points such as number of fish, average weight per fish, salmon biomass and number of fish dead. The corresponding disease data contains 25000 weekly data points such ass weekly sea lice level and record of PD and ISA infections.

4.2 Early harvest risk

Early harvest risk is one of the main components in our proposed BIP-model. This risk can force the farmer to harvest its stock prematurely and as mentioned in Section 1, consequences of this risk is low harvested salmon weight which leads to a significant lower revenue compared to the expected revenue. Early harvest risk is, therefore, considered as one of most critical risks for a fish farmer. In this section, we first present the risk characteristics at the different production areas with respect to the factors which can trigger early harvest: Sea lice level, PD and ISA. Then we illustrate evidence of early harvest risk with the historical distribution of harvested weight of salmon. Thereafter, we investigate the development dynamics of PD, ISA and sea lice.

4.2.1 Risk characteristics

In 2017 the framework for the future growth of the Norwegian aquaculture industry, traffic light system, was introduced (Ministry of Trade, Industry and Fisheries, 2017; PwC Norway, 2017). It divides the Norwegian coastline into thirteen production areas, and each area assigns an either green, yellow or red color based on the growth indicator which currently is only based on the risk of mortality of wild salmon due to lice. In addition, a new regulation regarding PD with the goal of reducing the consequences of the disease and preventing it from spreading has also been introduced. This regulation divides Norway into three areas: Two no-PD zones that go from the border with Sweden in the south to Jærens Rev, and from Flatanger to the border to Russia in the north, and one PD zone which goes from Jærens Rev to Flatanger ("Forskrift om tiltak for å forebygge, begrense og bekjempe pankreassykdom (PD) hos akvakulturdyr", 2017). In the PD zone the occurrence of PD is much more common in PD zone than in the no-PD zones. To prevent spreading of PD in the no-PD zones when PD is detected, the regulations regarding forced harvest is much stricter in the no-PD zones.

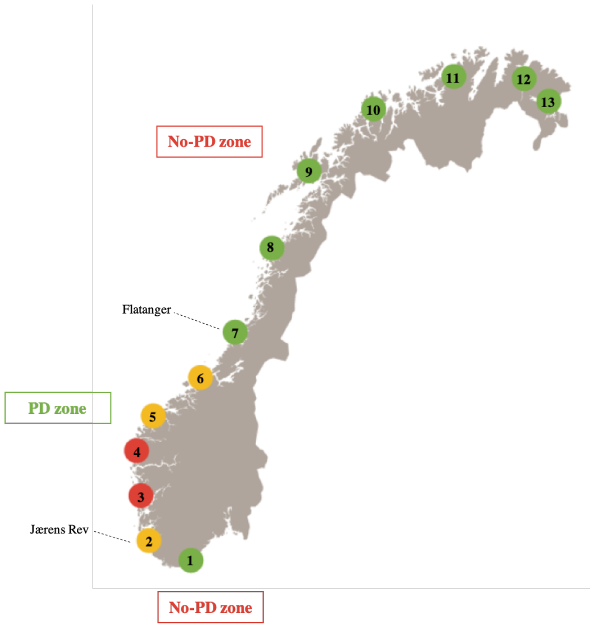


Figure 4.2: Overview of the "traffic lights" given to different production areas in 2017.

Figure 4.2 shows the PD zone and the two no-PD zones, as well as the thirteen production areas in Norway with their traffic light color. From this figure we can see that P3, P6 and P9 have red, yellow and green traffic light colors, respectively. We should, therefore, expect to see highest sea lice levels in P3, and lowest in P9. Next, P3 and P6 are located in a PD zone and P9 is located in a no-PD zone. Thus, we should expect to see higher rates of PD in P3 and P6 compared to P9.

Figure 4.3 gives an overview of the share of production weeks over the sea lice threshold, the share of production cycles with PD and ISA per production area; they are calculated based on the production and disease data.

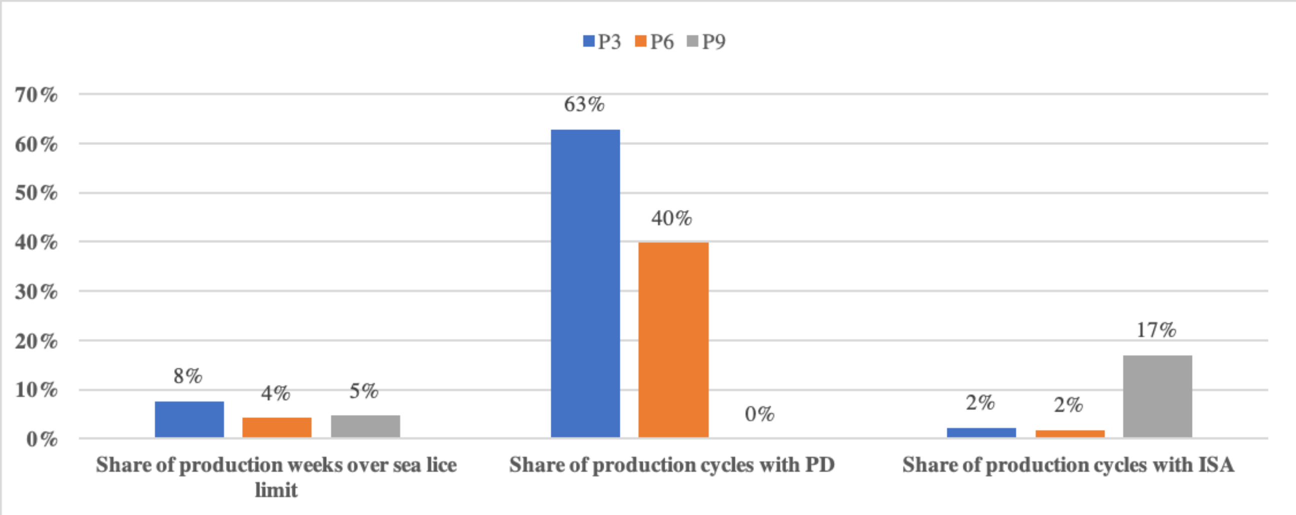


Figure 4.3: Risk characteristics regarding sea lice, PD and ISA in P3, P6 and P9.

Note that the share of production cycles over the sea lice threshold is about twice as high in P3 compared to two other production areas. This is consistent with P3 has a red traffic light color. Next, PD is a rather widespread disease in P3 and P6 while in P9, which is in the no-PD zone, there is no occurrence of PD. When it comes to ISA, however, farmers in P9 are about 8.5 times more likely to get ISA than in any of the two other areas. An interesting observation here is that, despite all these production areas are located within the same country, the risk characteristics differ from production area to production area.

4.2.2 Distribution of harvested weight

Data of harvested salmon is not part of the production data sent from the farmers to the NDF, but the total number of fish at each location is. We have, therefore, estimated the harvesting distribution based on stock reduction data. We have identified four causes for stock reductions: (1) harvest, (2) strategic movement of stock, (3) escapes, and (4) counting errors. Escapes and counting errors are likely to have low effect on the distribution because the magnitude and frequency of those are too low. According to NDF, the average number of escapes per year in Norway in the period 2011 to 2018 was only 171.000 fish (Directorate of Fisheries, 2019), and it is, therefore, reasonable to assume that stock changes due these factors are insignificant. Next, since the data is already cleaned for production cycles with lower than six months estimated production times, there will likely be few, if any, strategic movements data in the data set. It is, therefore, reasonable to assume that harvest distribution estimation will give a relatively precise view of the true historical distribution of harvested average salmon weight.

Figure 4.4, 4.5 and 4.6 show the distribution of harvested average salmon weight. From a visual inspection, one can see that the distributions differ quite a lot from production area to production area, which speaks in favor of the use of historical simulation rather than a parametric model as has been pointed out in Section 2. Next, it is worth noticing the considerable share of the harvest at relatively low weights, which indicates that the early harvest risk is a serious risk in the aquaculture industry.

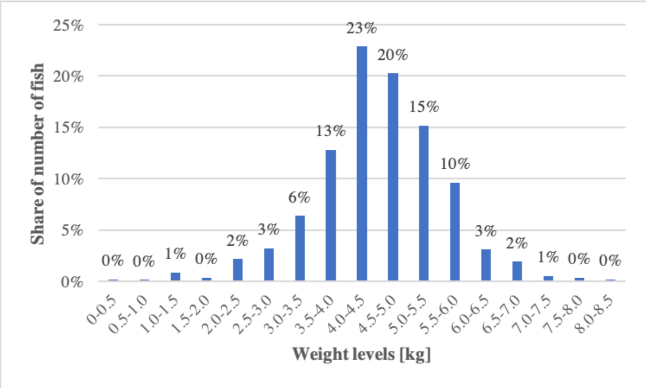


Figure 4.4: Estimated harvest distribution for P3.

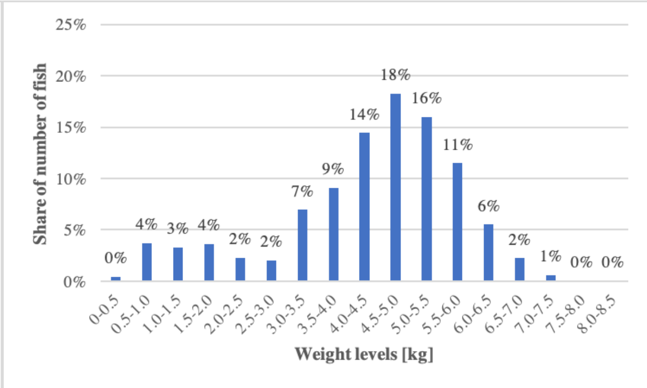


Figure 4.5: Estimated harvest distribution for P6.

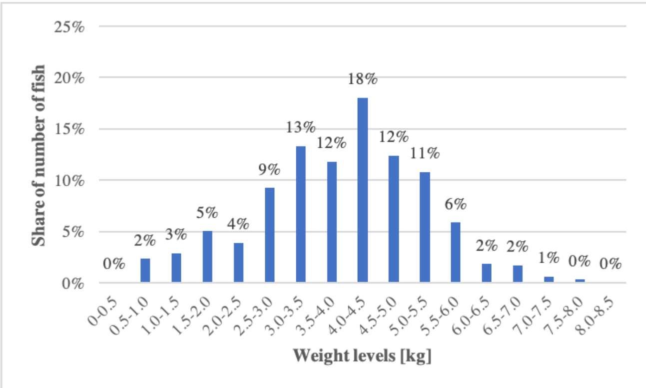


Figure 4.6: Estimated harvest distribution for P9.

Table 3 shows the 5% and 10% percentiles for estimated harvest distributions above. This table shows that the percentiles to P6 and P9 is lower than the percentiles to P3.

Percentile	P3	P6	P9
5%	2.5 kg-3.0 kg	1.0 kg - 1.5 kg	1.0 kg - 1.5 kg
10%	3.0 kg-3.5 kg	1.5 kg - 2.0 kg	1.5 kg - 2.0 kg

Table 3: Percentiles to the estimated harvest distributions in Figure 4.4, 4.5 and 4.6.

Based on Figure 4.3, P3 is the area that struggles the most with sea lice and PD. However, according to Table 3, P3 has the lowest early harvest risk among the production areas. This could indicate that NDF does not strictly enforcing the sea lice- and PD-policies.

4.2.3 Dynamics of PD and ISA development

When studying the dynamics of PD and ISA, we compare the characteristics of production cycles that are non-disease infected(healthy) and disease infected by PD or ISA. The disease data shows that once PD or ISA is recorded at a specific time during the production cycle, the cycle will remain recorded as infected until the production cycle has ended. We assign binary value 1 to infected production cycles and 0 to healthy cycles where neither PD or ISA has been recorded. We compare the healthy cycles to PD or ISA infected cycles on the following five production characteristics:

1. Autumn/spring production: The production is grouped into either autumn or spring production based on which month the production starts. This categorization has also been used in Kristoffersen et al. (2009) and Lyngstad et al. (2018) where Autumn production is between August and Feburary and spring production is between March and July. We assign binary value 1 to production cycles which are autumn production and 0 otherwise.
2. Smolt weight: The production is grouped based on the average weight of the fish being released into production. We classify whether the production uses smolt that are smaller than 99 grams or larger than 99 grams. This classification has been done similarly in McClure et al. (2005). We assign binary value 1 to production cycles which use smolt weight less than 99g, 0 otherwise.
3. Number of production months: During each production cycle, smolts can be released and biomass can be harvested at different points in time. In order to calculate the correct number of production months for each production cycle, we use a weighted average of production stop-time based on number of fish being harvested at each stop-time. In short, if half of the fish during a production cycle is harvested after 10 months and the rest is harvested after 20 months, the number of production months is calculated as 15 months.
4. Harvested average weight per fish: Biomass can be harvested at different points in time during each production cycle, here we use a weighted average of production stop-weight to calculate the correct harvested average weight per fish. In short, if half of the fish during a production cycle is harvested with average weight per fish at 2kg and the rest is harvested at 5kg, the harvested average weight is calculated 3.5kg.
5. Sea lice level: The number of adult female sea lice per fish is reported weekly during a production cycle. We calculate the sea lice level by taking average of reported data on number of adult female sea lice.

The descriptive statistics of the five above production characteristics are presented below in Figure 4.7 and 4.8. When we compare the healthy production cycles to the disease infected ones, we apply one-sided t-tests on the statistics which can be analyzed using hypothesis testing. Where null hypothesis is that the production characteristic under testing is equal between healthy and disease infected production cycles. Alternative hypothesis is formulated based on existing studies on how PD and ISA disease affect salmon fish (Aldrin et al., 2015; Costello, 2006), for example harvested average weight per fish is lower and sea lice level is higher with disease infected production cycles than healthy cycles.

Figure 4.7 displays a summary of descriptive statistics and comparing PD infected production cycles to normal production cycles in P3, P6 and P9. We see that PD is most severe in P3 especially in recent years where 70% of completed production cycles between 2015-2018 are infected. The PD infection occurrence in P6 is less severe compared to P3, however PD occurrence has been volatile ranging from 21% to 54% between 2015-2018. P9 is situated in non-PD zone where PD has not been detected at least in the last six years.

Production characteristics		Production area 3			Production area 6			Production area 9			Aggregated		
		Healthy cycles	PD cycles	Share of cycles with PD	Healthy cycles	PD cycles	Share of cycles with PD	Healthy cycles	PD cycles	Share of cycles with PD	Healthy cycles	PD cycles	Share of cycles with PD
Year harvested	2013	13	4	24%	8	2	20%	2	0	-	23	6	20%
	2014	21	25	54%	6	13	68%	6	0	-	33	38	52%
	2015	12	28	70%	19	5	21%	7	0	-	38	33	43%
	2016	14	32	70%	10	7	39 %	5	0	-	29	39	57%
	2017	13	29	67%	16	7	30%	10	0	-	39	36	47%
	2018	11	26	70%	11	13	54%	8	0	-	30	39	57%
Cycle characteristics	Autumn	32	64	66%	27	14	34%	11	0	-	70	78	52%
	Spring	52	80	60%	43	33	43%	27	0	-	122	113	47%
	Smolt weight ≤99g	8	22	73%	10	9	47%	10	0	-	28	31	50%
	Smolt weight >99g	76	122	61%	60	38	38%	28	0	-	164	160	48%
Number of production months	Mean	16.36	16.83	-	17.23	17.37	-	18.15	-	-	17.05	16.97	-
	Std.	1.91	1.89	-	1.71	1.73	-	2.73	-	-	2.13	1.87	-
Harvested average weight per fish (g)	Mean	4510	4556	-	4715	4624	-	4091	-	-	4501	4572	-
	Std.	735	740	-	641	850	-	687	-	-	724	766.54	-
Sea lice level	Mean	0.21	0.20	-	0.15	0.13	-	0.14	-	-	0.17	0.18	-
	Std.	0.12	0.11	-	0.09	0.07	-	0.08	-	-	0.11	0.11	-

Figure 4.7: Summary of PD dynamics.

Aldrin et al. (2015) suggests that PD disease reduces the appetite and growth of the salmon host, we use one sided t-test to see if this is the case with our data. As alternative hypothesis, we have harvested average weight per fish is lower with PD infected cycles than healthy cycles. According to the p-values from the t-test on weight in Table 4, we can not reject the null hypothesis and accept the alternative hypothesis even at a significance level as high as 0.1. This is the same for both when data from the three production areas are aggregated and when each production area is considered individually.

Production characteristics	P3	P6	P9	Aggregated
Number of production months	0.04	0.33	-	0.65
Harvested average weight per fish (g)	0.67	0.27	-	0.82
Sea lice level	0.73	0.94	-	0.16

Table 4: P-values of one sided t-test on the means between healthy and PD infected production cycles in Figure 4.7.

To check if this is due to prolonged production length, we perform one sided t-test with number of production months is larger with PD infected production cycles as alternative hypothesis. Table 4 shows that we can accept the alternative hypothesis at a significance level 0.05 for P3. The result, thus, suggest that in P3 where PD infection is most severe, prolonged production time is needed when a cycle is infected by PD in order to achieve the same harvested weight of salmon as when the cycle is healthy. In other words, data from P3 confirms the finding in Aldrin et al. (2015). In light of regulations imposed by the NFSA, the p-values form the t-test on number of production months indicate that despite the authority can force early harvest of biomass when PD infected, the biomass is however, allowed to continue growing as usual. This confirms our observation in Section 4.2.2 regarding possible non-enforcement of PD. The finding in Costello (2006) shows that sea lice infestation makes salmon more susceptible to disease. To investigate if sea lice level is higher with PD infected production cycles, again we use one tailed t-test. The p-values from Table 4 suggest that we can not accept the alternative hypothesis that PD infected production cycles has higher sea lice level even at significance of 0.1. In the attempt to identify risk factors to explain the occurrence of PD disease nationwide by Kristoffersen et al. (2009), one significant factor was whether the production starts with autumn smolts. In their study 20% of the cycles with autumn smolts were PD infected against 12% with spring smolts. Kristoffersen et al. (2009) elaborates that autumn smolts are smaller and are thus more susceptible to disease. Figure 4.7 shows that our result coincides with the finding in Kristoffersen et al. (2009) on an aggregated level, a higher share of production cycles have recorded PD when production uses smaller smolts, less than 99g, and when production starts in autumn. When looking at P3 and P6 separately, PD infection in P3 may be affected by autumn production, however, in P6 it tends more toward spring production. This observation shows there may exist regional differences to what contributes to infection of PD and it motivates to model the probability of PD occurrence per region as apposed to on an aggregated level. As mentioned in Section 3.1, probability occurrence of PD will be modeled using logistic regression model. Later in Section 5, four of the five above mentioned production characteristics will be used as potential explanatory variables in the logistic model for PD.

Compared to PD, ISA occurs rarely, only 15 cases against 191 PD cases in the same observation period for P3, P6 and P9. Figure 4.8 shows, the majority of ISA infected production cycles are recorded in P9, but in the last three years, more cycles are being infected with ISA in P3.

Production characteristics		**Production area 3**			**Production area 6**			**Production area 9**			**Aggregated**		
		Healthy cycles	**ISA cycles**	**Share of cycles with ISA**	**Healthy cycles**	**ISA cycles**	**Share of cycles with ISA**	**Healthy cycles**	**ISA cycles**	**Share of cycles with ISA**	**Healthy cycles**	**ISA cycles**	**Share of cycles with ISA**
Year harvested	2013	13	0	-	8	0	-	2	1	33%	23	1	3 %
	2014	21	0	-	6	0	-	6	2	25%	33	2	3 %
	2015	12	0	-	19	1	4%	7	5	41%	38	6	8 %
	2016	14	0	-	10	1	5%	5	0	-	29	1	1 %
	2017	13	2	4%	16	0	-	10	0	-	39	2	3 %
	2018	11	3	8%	11	0	-	8	0	-	30	3	4 %
Cycle characteristics	Autumn	32	3	3%	27	0	-	11	2	15%	70	5	3%
	Spring	52	2	2%	43	2	3%	27	6	18%	122	10	4%
	Smolt weight ≤99g	8	1	3%	10	0	-	10	3	23%	28	4	6 %
	Smolt weight >99g	76	4	2%	60	2	2%	28	5	15%	164	11	3 %
Number of production months	Mean	16.36	14.28	-	17.23	15.66	-	18.15	13.85	-	17.05	14.23	-
	Std.	1.91	0.76	-	1.71	0.2	-	2.73	2.97	-	2.13	2.23	-
Harvested average weight per fish (g)	Mean	4510	3184	-	4715	4680	-	4091	2509	-	4501	3023	-
	Std.	735	842	-	641	118	-	687	1023	-	724	1131	-
Sea lice level	Mean	0.209	0.161	-	0.149	0.139	-	0.141	0.164	-	0.173	0.16	-
	Std.	0.117	0.063	-	0.088	0.138	-	0.081	0.152	-	0.105	0.119	-

Figure 4.8: Summary of ISA dynamics

We also see in Figure 4.8 that both number of production months and harvested average weight per fish are less with ISA infected production cycles than healthy. Explanation for this is a very strict regulation by NFSA which forces farmers to almost immediately harvest all salmon on production site when proven to be ISA infected (Norwegian Food Safety Authoriy, 2018b), resulting in insufficient growth of salmon and thus low salmon weight. To investigate the significance, we perform one tailed t-test with alternative hypothesis that number of production months is shorter and harvested average weight per fish is lower with ISA infected production cycles than healthy cycles. Table 5 displays the resulting p-values from the t-tests and it shows that we can accept the alternative hypothesis at a significance level of 0.05, except for harvested average weight for P6.

Production characteristics	**P3**	**P6**	**P9**	**Aggregated**
Number of production months	<0.01	0.05	<0.01	<0.01
Harvested average weight per fish (g)	0.01	0.40	<0.01	<0.01
Sea lice level	0.10	0.47	0.63	0.34

Table 5: P-values of t-test on the means between healthy and ISA infected production cycles in Figure 4.8.

One explanation for this exception is lack of ISA occurrence in the data, which results in we can not rule out the possibility that the only two ISA infections in P6 are two outliers of ISA production cycles. Figure 4.8 also shows the p-values for one tailed t-test on sea lice level between ISA infected production cycles and healthy cycles. The p-values suggest we keep the null hypothesis that the sea lice level are equal. Lyngstad et al. (2018) and McClure et al. (2005) are two examples of attempts on explaining the occurrence of ISA. McClure et al. (2005) discovered that the smolt weights larger than 99g increases the probability of ISA occurrence. Our result indicates, however, a higher share of production cycles are ISA infected when smolts are smaller than 99g. Possible reasons for this mismatch are geographical differences and timing of the study by McClure et al. (2005). The study was carried out in 2005 on the data material which is extracted from Canadian production sites. In addition, ISA occurred more frequently in the study period in McClure et al. (2005) compared to ours. The finding in the nationwide study by Lyngstad et al. (2018) suggests that neither autumn nor spring production affects the probability of being ISA infected. Our result shows that when data from P3, P6 and P9 are aggregated, there is a slightly higher share of production cycles being ISA infected when spring production is being carried out. Looking at P3 separately, it displays the opposite. As with PD dynamics, this observation also suggests that there are potential regional differences regarding what governs occurrence of ISA which should be accounted. As with PD, probability occurrence of ISA will be modeled using logistic regression model. Later in Section 5, four of the production characteristics will be used as potential explanatory variables in the logistic model for ISA.

4.2.4 Dynamics of sea lice development

As mentioned in Section 2, there exist several studies on how to model sea lice development dynamics; however, very few include the impact of sea lice treatments. The sea lice is a parasite that grows exponentially as a function of its population when it is not treated (Costello, 2006). In contrast to PD and ISA, there exist many different treatments for sea lice, however, in return the farmer has to expect a higher mortality rate (Liu & Bjelland, 2014). The farmer is, therefore, hesitant to treat the fish at low sea lice levels. Thus, we expect that the sea lice to grow freely and unaffected at low sea lice levels. Once the average number of female sea lice per fish has reached 0.5, the farmer is obliged to either treat the fish or harvest it within two weeks (Heuch et al., 2005). Since the sea lice level can reach this threshold early in the production cycle, the farmer will have a strong incentive to accept higher mortality rates and treat the stock in order to prevent an early harvest. Thus, we could expect to see a large number of negative sea lice growth rates when sea lice level is above the threshold. In between the low sea lice levels and above the threshold, the farmers have to make treatment decisions on whether to conduct preventative sea lice treatments or not. These decisions are to be different for different farmers

We define delta sea lice level as absolute change in sea lice level where positive delta means increase in sea lice level, negative delta means decrease and zero delta means no change. Figure 4.9 displays the average delta at different sea lice levels for each production area.

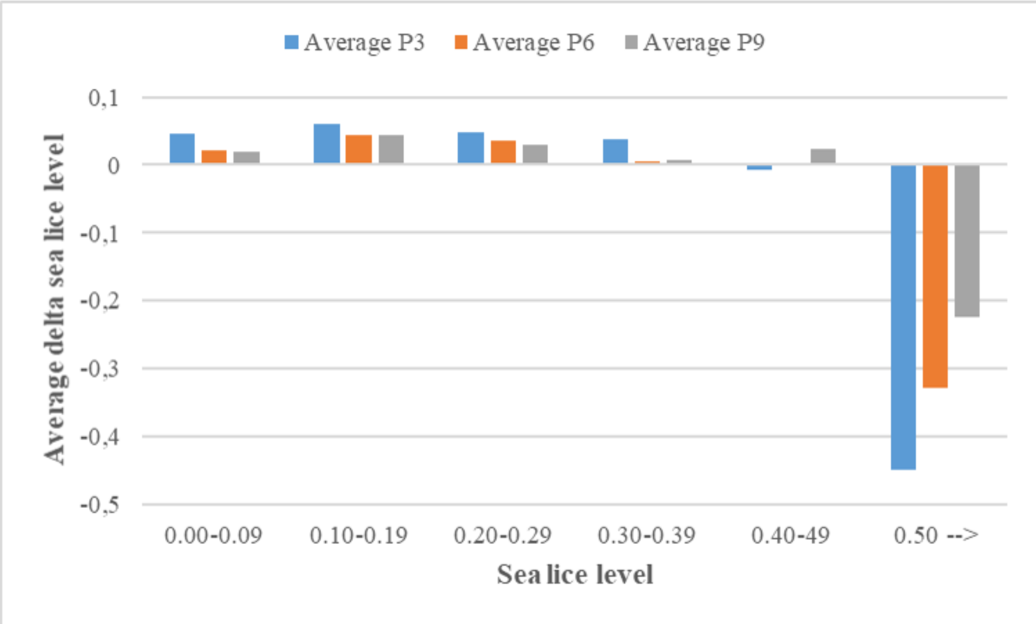


Figure 4.9: Average delta sea lice level per sea lice level.

Figure 4.9 shows that as soon as the sea lice level has breached the threshold of 0.5, the average deltas drops significantly. Next, Figure 4.10 shows the standard deviation of the deltas for each region at different sea lice levels.

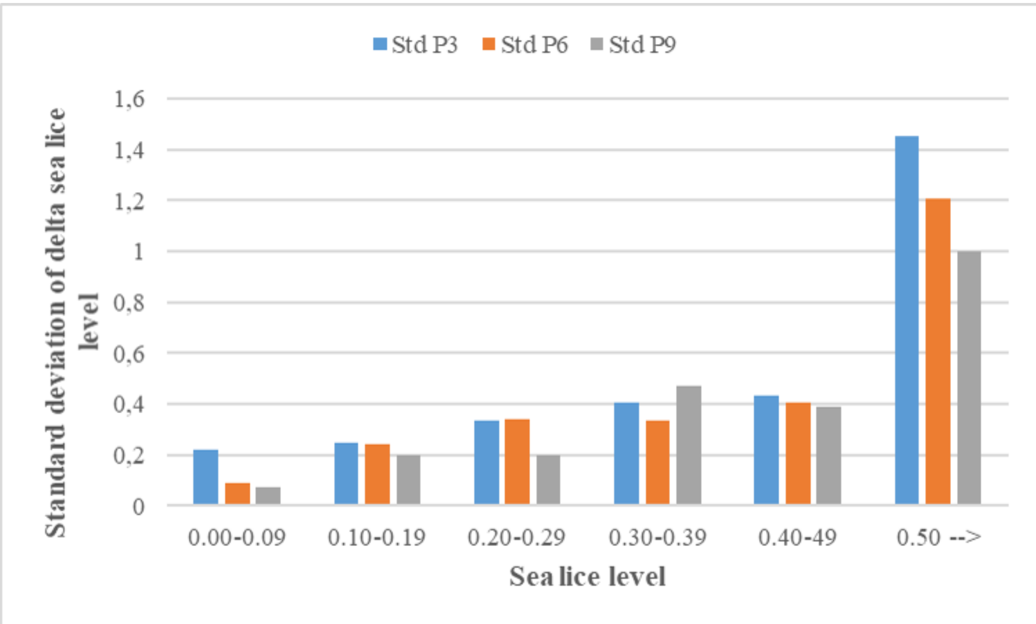


Figure 4.10: Standard deviation of delta sea lice level per sea lice level.

Based on visual inspection, this figure indicates that the standard deviation increases with the sea lice level, which would be consistent with different strategies for sea lice treatments among the farmers. Further, Figure 4.11 shows the share of positive deltas, negative deltas, and zero deltas which stand for no changes in sea lice level. The data is color formatted in Microsoft Excel with green-yellow-red, where green represents low values, and red represents high values.

Sea Lice level	Share of positive deltas			Share of negative deltas			Share of deltas equal zero		
	P3	P6	P9	P3	P6	P9	P3	P6	P9
0.00-0.09	40 %	37 %	34 %	17 %	21 %	18 %	43 %	42 %	48 %
0.10-0.19	53 %	47 %	49 %	40 %	46 %	40 %	6 %	7 %	11 %
0.20-0.29	46 %	42 %	51 %	47 %	52 %	46 %	7 %	6 %	3 %
0.30-0.39	44 %	40 %	40 %	52 %	54 %	55 %	4 %	6 %	4 %
0.40-49	32 %	30 %	38 %	62 %	66 %	54 %	5 %	4 %	8 %
0.50 -->	26 %	26 %	30 %	70 %	72 %	65 %	4 %	2 %	5 %

Figure 4.11: Table of positive deltas, negative deltas and deltas equal to zero per sea lice level.

Figure 4.11 shows that when sea lice level is at 0.00-0.09, the share of zero deltas is four to six times higher than other sea lice levels. Intuitively, when there is no sea lice or sea lice level is close to zero, reproduction of sea lice is very limited. Figure 4.11 also shows that the share of negative deltas at the same sea lice level, 0.00-0.09, is significantly lower than other sea lice level. This confirms our expectation stated in the beginning of this section, that farmers are hesitant to conduct sea lice treatments at low sea lice levels due to the risk of getting higher mortality rates. Figure 4.11 also displays that share of positive and negative deltas change as sea lice level increases. This finding show that sea lice develops differently at different sea lice levels and this suggests sea lice follows a path dependent development. To illustrate, if sea lice level is high today, Figure 4.11 shows that there is a higher probability that the sea lice level tomorrow will go down then up. Vice versa if the sea lice level is low today.

To incorporate identified dynamics of sea lice growth, we use a regime shift model in the historical simulation to describe the sea lice development. To take into account the large negative deltas when sea lice level is above 0.5, as shown in Figure 4.9 and large share of zero deltas when sea lice level is low, as shown in Figure 4.11, we propose 3 regimes where the first regime is from sea lice level 0.00-0.09, the third regime is when sea lice level above 0.5 and the second regime is in between. Figure 4.12 illustrates the proposed three regimes.

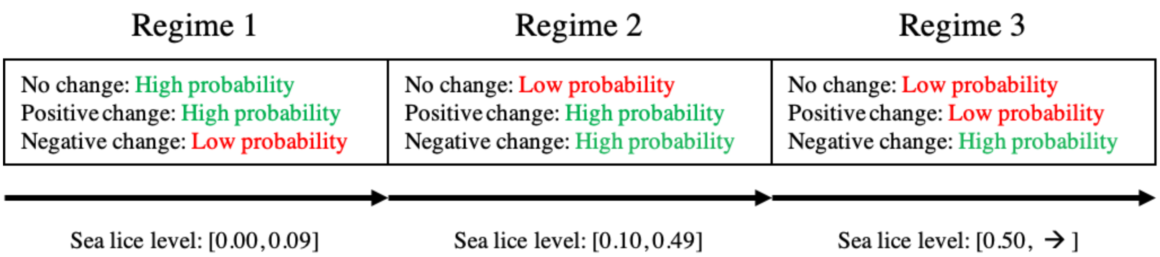


Figure 4.12: Regime shift model of sea lice development.

We have conducted t-tests on the averages, and F-tests on the variances with a null hypothesis that the averages and variances between the regimes are equal and an alternative hypothesis that they are different. These tests were performed between every regimes in the proposed models, and its results are presented in Figure 4.13. This figure shows that the f-tests strongly rejects the null hypothesis (p-value $< < 0.01$) of equal variances between all of the regimes.

Production area	Regime	Average delta sea lice	Std. delta sea lice	P-values from t-test P12	P-values from t-test P13	P-values from t-test P23	P-values from f-test P12	P-values from f-test P13	P-values from f-test P23
Production area 3	1	0,046	0,222						
	2	0,043	0,336	0,571	0,000	0,000	0,000	0,000	0,000
	3	-0,448	0,431						
Production area 6	1	0,021	0,089						
	2	0,031	0,306	0,092	0,000	0,000	0,000	0,000	0,000
	3	-0,328	1,207						
Production area 9	1	0,019	0,072						
	2	0,031	0,287	0,205	0,003	0,002	0,000	0,000	0,000
	3	-0,225	1,000						

Figure 4.13: P-values of t-test and F-test results regarding regime shifts in sea lice development.

The t-tests rejects the null hypothesis of equal averages between regimes for P6 at significance level of 0.1. At the same significance level, for P3 and P9, the p-values are not large enough to reject the hypothesis of equal averages between regimes. However, dynamics of the sea lice development is described with more than just the average. Based on a combination of visual inspection of Figure 4.11 and significant differences in variances between regimes for P3 and P9, we keep the proposed regimes for both production areas. When using historical simulation in the third regime, to better mirror the decrease in sea lice level as a result of initiated treatment and avoid spurious decrease, we draw relative changes in sea lice level instead of absolute changes. This reduces the risk of simulating unrealistically low treatment success ratios.

4.3 Mortality

The mortality rate is one of the two components that govern the size of the biomass at each given time in the BIP model. It determines the number of fish in the sea pen from month to month. Several studies claim the post-smolt mortality rates are expected to be most severe in the first couple of months (Eriksson, 1994; Fisher & Pearcy, 1988; K. D. Friedland, Hansen, Dunkley, & MacLean, 2000; Holtby, Andersen, & Kadowaki, 1990; Salminen, Kuikka, & Erkamo, 1995). During this period, the higher mortality rates are related to the smolt adjusting to the new ocean climate, interspecific competition, and intraspecific interactions (K. Friedland, 1996; L'Abée-Lund, Langeland, Jonsson, & Ugedal, 1993; Neilson & Geen, 1986; Ricker, 1962). Furthermore, due to environmental challenges with medical treatment of sea lice, and the increased resistance to these treatments, the fish farmers have focused more on mechanical treatment in the last decade. During the mechanical treatments, the salmon is experiencing a lot of stress, and, according to Overton et al. (2018), the risk of higher mortality rates increases. It is reasonable to assume that the sea lice treatment increases with the production time in order to cope with the rising sea lice level. We could, therefore, expect to see higher mortality rates towards the end of the production cycle. Based on the findings from literature we expect high mortality rates at the beginning of each cycle, followed by a period with less mortality, finishing the cycle with a period with higher mortality rates again.

	Average mortality rate			Standard deviation mortality rate		
Production Month	**Production area 3**	**Production area 6**	**Production area 9**	**Production area 3**	**Production area 6**	**Production area 9**
1	1,10 %	1,74 %	1,55 %	3,15 %	3,72 %	3,24 %
2	0,61 %	1,54 %	1,41 %	2,14 %	3,24 %	1,82 %
3	0,51 %	1,09 %	1,26 %	1,19 %	1,96 %	3,31 %
4	0,74 %	0,82 %	0,72 %	1,71 %	1,26 %	0,99 %
5	0,81 %	1,00 %	0,59 %	1,52 %	1,63 %	0,60 %
6	0,81 %	0,75 %	0,62 %	1,63 %	1,09 %	0,62 %
7	1,12 %	0,65 %	0,46 %	2,08 %	0,79 %	0,33 %
8	1,42 %	0,58 %	0,54 %	3,89 %	0,68 %	0,42 %
9	1,00 %	0,55 %	0,77 %	1,58 %	0,78 %	0,68 %
10	1,34 %	0,62 %	1,07 %	2,47 %	1,03 %	0,52 %
11	1,39 %	0,69 %	0,65 %	2,43 %	1,42 %	0,87 %
12	1,84 %	0,78 %	0,91 %	3,19 %	1,04 %	1,60 %
13	2,40 %	1,29 %	1,56 %	5,89 %	2,42 %	2,86 %
14	2,13 %	1,58 %	0,60 %	4,62 %	2,35 %	1,15 %
15	1,93 %	1,48 %	0,87 %	3,26 %	2,10 %	1,73 %
16	1,90 %	1,61 %	0,71 %	4,10 %	1,89 %	1,20 %
17	2,20 %	2,23 %	0,84 %	3,75 %	4,66 %	1,70 %
18	1,84 %	1,97 %	0,69 %	2,52 %	2,42 %	0,81 %
19	2,10 %	1,83 %	0,76 %	2,08 %	2,14 %	1,42 %
20	2,00 %	2,66 %	0,77 %	1,87 %	3,93 %	1,51 %

Figure 4.14: Overview of average and standard deviation of mortality rates data for P3, P6 and P9.

Figure 4.14 shows the expected mortality rates and standard deviation of the mortality rates per production month in each region. The data is color formatted in the same way as Figure 4.11. As expected, we observe higher mortality rates towards the end of the production cycle in all of the regions. In the first couple of months, however, we only see higher mortality rates in two out of three production areas. One possible explanation for the low mortality rates in P3 at the first couple of months of the production cycle might be use of post-smolt production. According to Terjesen (2014), the use of post-smolt production will make the salmon more robust before entering the sea and thereby increase the survival rate in the first couple of months.

Next, it is worth noticing the clustering of high standard deviations in mortality rates in the first couple of months and towards the end of the production cycle. A possible explanation behind this observation might be different strategies in sea-lice treatments among the farmers. For example, different strategies with the use of post-smolt technologies could explain the clustering at the start of the cycle. Those who use post-smolt technologies will likely have lower mortality rates at the start of the cycle compared to those who do not use this technology, leading to high standard deviation.

Our findings suggest the use of a regime shift model in the historical simulation with two regimes for P3, and three regimes for P6 and P9. We have, therefore, conducted a Chow test on the accumulated mortality and the standard deviation of mortality rates to test whether there is a structural break in the mortality rates or not. The tests were performed with the null hypotheses that the regression parameters in the different regimes are equal, and with the alternative hypothesis that they are unequal. For the purpose of this paper it is adequate to find a regime shift model that in a large extent succeeds in modeling the key characteristics of the data. We have, therefore, defined and tested a regime shift model that is solely based on a visual inspection of Figure 4.14, which is illustrated in Figure 4.15. Table 6 shows that the test on accumulated mortality strongly rejects the null hypothesis for P3 and P6 with p-values equal to 0.000. However, with an p-value of 0.117 for P9, the test fails to strongly reject the null hypothesis. For the structural break test on standard deviation the test strongly rejects the null hypothesis for all of the regions with p-values equal to 0.036, 0.000 and 0.000 for P3, P6 and P9 respectively. This result supports the use of a regime shift model as suggested, and are, therefore, included in the simulation of the mortality rates in the BIP model.

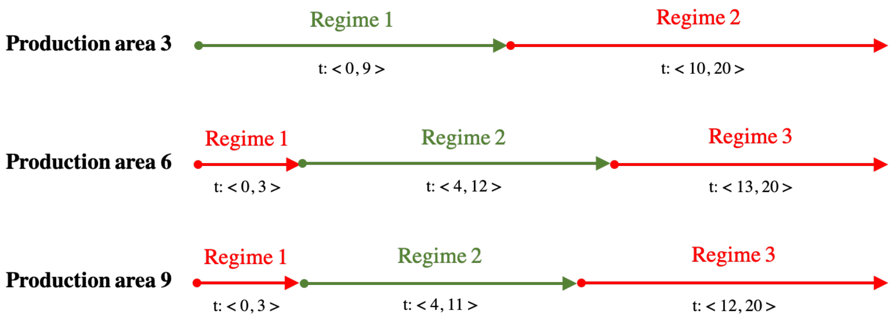


Figure 4.15: Proposed regime shift model for P3, P6 and P9 for mortality rates.

Production areas	Accumulated mortality	Standard deviation on mortality rate
P3	0.000	0.036
P6	0.000	0.000
P9	0.117	0.000

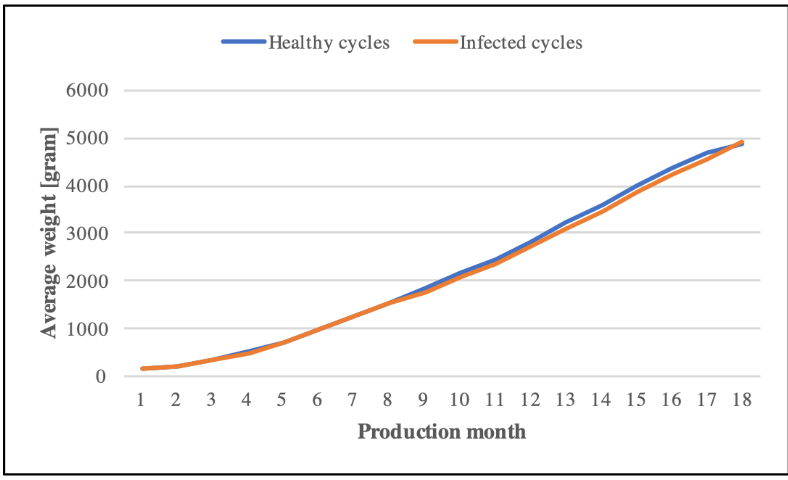
Table 6: P-values from Chow test on the proposed regimes illustrated in Figure 4.15.

Further, the mortality is also affected by which sea lice treatments (Liu & Bjelland, 2014) and feeding regimes (Damsgård et al., 2004) that are used. Thus, it is reasonable to assume that the mortality dynamics might differ between the farmers within each production area.

4.4 Weight development dynamics

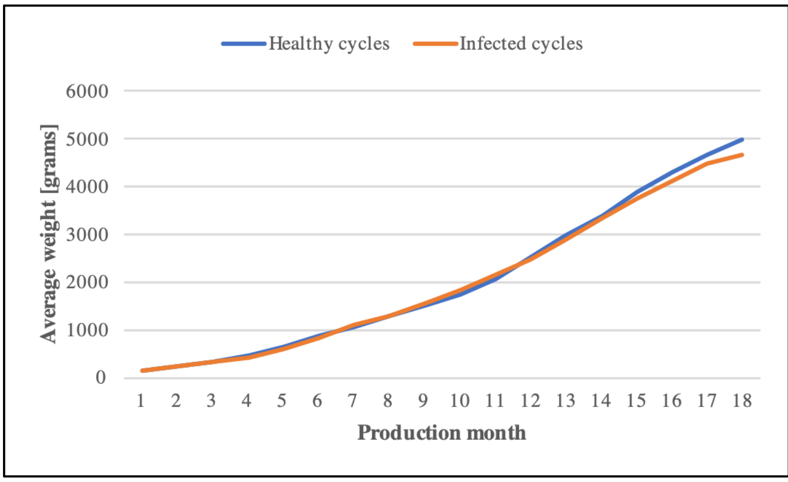
The weight of the fish is the second component that governs the size of the biomass at each given time in the BIP model. The literature suggests that diseases such as PD and ISA reduces the appetite and the growth rate of the host (Aldrin et al., 2015; Costello, 2006; Damsgård et al., 2004; Liu & Bjelland, 2014). Thus, it is reasonable to assume that infected fish has slower weight development compared to healthy fish. However, regulations can force farmers to harvest prematurely if these diseases are detected. Therefore, the infections might not have enough time to significantly influence the weight development before the fish is harvested. If the disease has a significant impact on the average weight development of the fish, it is reasonable to split the data set into healthy- and infected-production cycles when modeling the weight development.

To test if the data set should be split into healthy and infected production cycles, we have conducted a t-test on the average weight of production cycles with infected fish and production cycles with no infected fish, with the null hypothesis that the averages weights er equal, and alternative hypothesis that the average weights of healthy production cycles are larger than the average weight of infected production cycles. The t-test were performed on every production month in all of the production areas. Every production cycle that were infected by either PD and/or ISA were defines a infected production cycle, regardless of when in the production cycle the infection were detected. Figures 4.16, 4.17 and 4.18 shows the weight development of production cycles with and without detected diseases, and the p-values from the t-test for each month. There is only a small fraction of the p-values that strongly rejects the null hypothesis in P3 and P6, and none in P9. An interesting observation from Figure 4.18 is that the average weight of the infected cycles is actually higher for most of the months; however, this production area had only nine infected cycles, and, therefore, one should be cautious about making any conclusions based on this result. Due to the inability of the results from the t-tests to confirm that the infected production cycles has a lower weight development than healthy production cycles, we will not split the data set.



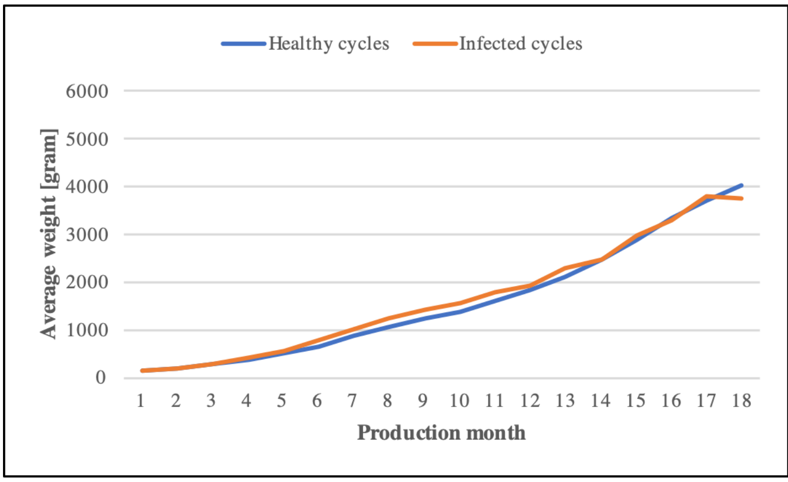
Production month	P-values
1	0,114
2	0,193
3	0,379
4	0,384
5	0,426
6	0,443
7	0,370
8	0,300
9	0,203
10	0,161
11	0,143
12	0,156
13	0,073
14	0,032
15	0,026
16	0,056
17	0,088
18	0,568

Figure 4.16: Overview of healthy vs infected weight development, and p-values of t-test in P3.



Production month	P-values
1	0,696
2	0,342
3	0,245
4	0,179
5	0,171
6	0,476
7	0,632
8	0,718
9	0,770
10	0,865
11	0,743
12	0,470
13	0,310
14	0,270
15	0,130
16	0,080
17	0,102
18	0,012

Figure 4.17: Overview of healthy vs infected weight development, and p-values of t-test in P6.



Production month	P-values
1	0,651
2	0,707
3	0,608
4	0,747
5	0,789
6	0,925
7	0,891
8	0,853
9	0,848
10	0,820
11	0,776
12	0,684
13	0,782
14	0,499
15	0,687
16	0,463
17	0,583
18	0,174

Figure 4.18: Overview of healthy vs infected weight development, and p-values of t-test in P9.

Further, the farmer has a direct impact on the growth rates of the fish (Jørgensen & Jobling, 1992). Thus, it is natural to assume that there could be differences in the weight development between the farmers.

5 Model estimation

In the previous section, we have identified appropriate regimes for sea lice development and mortality rates for our proposed model. We also discussed how one could argue that there could be differences in the weight- and mortality-development among farmers in the same region. However, due to a lack of data on a company level with a maximum of three succeeding production cycles for one company at one specific location, this was not investigated further. Thus, in this paper, we use regional level data when modeling the BIP-model. In this section, we first estimate the parameters of the logistic models which we use to describe the probability of PD and ISA occurrence. Afterwards, we estimate the VB-growth function which we use to describe weight development of salmon. In addition, we also calculate the proven yield weight which we use in our Monte carlo simulation.

5.1 Estimation of logistic model parameters

As mentioned in Section 3.1, we use logistic models to describe the probability of recording PD or ISA during a production cycle. Specifically, the probabilities are described by the two equations below:

$$P_{PD,z} = \frac{1}{1+e^{-z}}, \tag{11}$$

$$P_{ISA,w} = \frac{1}{1+e^{-w}}, \tag{12}$$

where $z = \alpha_0 + \alpha_1 x_1 + \cdots + \alpha_k x_k$ and $w = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$ are linear combinations of an intercept and a series of variables in explaining occurrence of PD and ISA. To simulate early harvest risk posed by PD and ISA, we estimate the probability of recording them at a certain time during production given PD or ISA actually occurs. Again, we use logistic models and production time t will be the only variable:

$$P_{t|PD} = \frac{1}{1+e^{-(\alpha_0+\alpha_1 t)}}. \tag{13}$$

$$P_{t|ISA} = \frac{1}{1+e^{-(\beta_0+\beta_1 t)}}. \tag{14}$$

To calculate the variable parameters in Equation 11, 12, 13 and 14, we maximize the following log-likelihood function:

$$LLF = -\sum_{i=1}^{i=N}[p_i ln(1+e^{-y_i}) + (1-p_i) ln(1+e^{y_i})]. \tag{15}$$

where i stands for the ith production cycle in data, p_i is the i'th binary observation of PD or ISA outbreak and $y_i = \gamma_0 + \gamma_1 x_1 i + \cdots + \gamma_k x_k i$ is a linear combination of an intercept and a series of variables under estimation. y_i can be univariate, for example $y_i = \gamma_0 + \gamma_1 x_{1,i}$. The significance of the n'th variable in the logistic regression is tested using likelihood ratio test and the test statistic follows:

$$LR_n = -2(LLF_{n,r} - LLF_{n,u}) \sim \chi^2(1). \tag{16}$$

$LLF_{n,u}$ is the maximized LLF value of the unconstrained model and $LLF_{n,r}$ is the new LLF value when $\gamma_n = 0$. The p-value is calculated form the chi-square distribution with one degree of freedom since there is only one restriction on the model. Both Equation 15 and 16 are presented in Brooks (2017). To decide which logistic model is the most appropriate one, we use Akaike Information Criterion:

$$AIC = 2k - 2LLF_k, \tag{17}$$

where k stands for number of parameters under estimation and LLF_k is the maximized loglikelihood function. AIC estimates the relative information being lost by using a given model, therefore the lower the AIC value the better. Based on Equation 17, AIC increases when the model is overfitted with the term $2k$, it does the same when the model is underfitted with the term $-LLF_k$. This statistic has also been used by Kristoffersen et al. (2009) and Lyngstad et al. (2018) when deciding the optimal combination of significant variables in their logistic regression models.

With the available data presented in Section 4.2.1, the following five variables are included as potential explanatory variables for the occurrence of PD and ISA during a production cycle. Number of production months(x_1), sea lice level(x_2), latitude(x_3), whether smolt weight is below 99 gram(x_4) and whether production is initiated during autumn(x_5). Definitions and descriptive statistics of the five above variables are stated in Section 4.2.1. In short, they describe production characteristics and geographical locations. Similar to Kristoffersen et al. (2009) and Lyngstad et al. (2018), we use forward selection to choose variables into the logistic model. In other words, potential variables are added in the order of their statistical significance as determined by univariate logistic regression. The combination of variables with the lowest AIC statistic is chosen as the optimal fitted logistic model.

For each production area, first we perform univariate logistic regression on our available production level data by using Equation 15 on $P_{PD} = \frac{1}{1+e^{-(\alpha_0+\alpha_1 x_i)}}$ and $P_{ISA} = \frac{1}{1+e^{-(\beta_0+\beta_1 x_i)}}$, for $i = 1, ..., 5$. Then we use Equation 16 to determine each variable's significance and Equation 17 to calculate AIC statistic. To exam if a multivariate model provides a better model fit, in other words a lower AIC, we add $x_1, ..., x_5$ in the order of their significance. Again Equation 15 and 17 are used on $P_{PD} = \frac{1}{1+e^{-(\alpha_0+\sum[\alpha_i x_i])}}$ and $P_{ISA} = \frac{1}{1+e^{-(\beta_0+\sum[\beta_1 x_i])}}$ to estimate parameters and calculate AIC statistic. In addition, we also calculate the AIC when there is only a constant included in $P_{PD} = \frac{1}{1+e^{-\alpha_0}}$ and $P_{ISA} = \frac{1}{1+e^{-\beta_0}}$. In the end, the model with lowest AIC statistic and variable parameters that make biological sense is chosen. The following figure presents the AIC statistic, and significance level and numerical parameter value of the variable in the chosen model which best describes the probability of PD and ISA occurrence in P3, P6, and P9. The single star above the parameter value in the figure represent the variable is significant at significance level of 0.1.

PD	Significant variable	α_0	α_1	AIC
P3	X_1	-1.80	0.14*	300
P6	X_3	-56.25	0.88*	158
P9	-	-	-	-
ISA	**Significant variable**	β_0	β_0	**AIC**
P3	-	-3.80	-	48
P6	-	-4.06	-	20
P9	-	-1.56	-	43

Figure 5.19: AIC statistic, significance level and numerical parameter values of the variables in logistic models describing the probability of occurrence of PD and ISA in P3, P6 and P9.

By inserting the above variable parameters into Equation 11 and 12, we have the following equations where probability of PD occurrence is best describes with univariate logistic model and ISA is best described with a constant.

$$P^{P3}_{PD,x_1} = \frac{1}{1 + e^{-(-1.80+0.14x_1)}}. \tag{18}$$

$$P^{P6}_{PD,x_3} = \frac{1}{1 + e^{-(-56.25+0.88x_3)}}. \tag{19}$$

$$P^{P3}_{ISA,x_1} = \frac{1}{1 + e^{-(-3.80)}} = 0.022. \tag{20}$$

$$P^{P6}_{ISA} = \frac{1}{1 + e^{-(-4.06)}} = 0.017. \tag{21}$$

$$P^{P9}_{ISA,x_1} = \frac{1}{1 + e^{-(-1.56)}} = 0.174. \tag{22}$$

Comparing to Kristoffersen et al. (2009); when describing the probability of occurrence of PD on a national level, both number of production months and distance between production cites in kms are part of the best fitted model according to AIC. Our results which are generated on a regional level, shows that number of production months is significant at a significance level of 0.05 and provides best model fit for P3 according to AIC. And, distance between sites in terms of geographical latitudes is significant significant at sigificance level of 0.1 and provides best fit according to AIC for P6. Comparing to Lyngstad et al. (2018), a nationwide study on the probability of occurrence of ISA, latitude is one of the significant variables in the best fitted model. In our case, the best fitted model to describe the probability of ISA occurrence in each production area is a constant. This constant probability is different for each region, therefore, our result actually supports the finding in Lyngstad et al. (2018) as probability of ISA occurrence differs depending on the geographical location.

In order to decide when salmon biomass is forced to be early harvested given PD and ISA occurs, we need to know the probability of recording PD or ISA at a specific time during production. Again, we use logistic regression, however, this time it will be only applied on the production cycles which have recorded PD or ISA. In this case, we are just interested in finding the probability which is connected to production time, therefore, we consider production time t in month as the only explanatory variable in an univariate logistic regression. For each production area, we use Equation 15 and 16 on $P_{t|PD} = \frac{1}{1+e^{-(\alpha_0+\alpha_1 t)}}$ and $P_{t|ISA} = \frac{1}{1+e^{-(\beta_0+\beta_1 t)}}$

to estimate variable parameter and to test variable significance. The figure below shows that production time is a significant variable with significance level below 0.001 in describing the PD and ISA occurrence at a specific time t during production given PD or ISA occurs. Due to lack of ISA occurrences in P6, Equation 15 failed to return a valid solution when estimating variable parameter to production time t. Instead, a constant probability is found and will be used.

PD	**Significance level of variable *t***	α_0	α_1
P3	<0.001	-5.71	0.54
P6	<0.001	-3.99	0.42
P9	-	-	-
ISA	**Significance level of variable *t***	β_0	β_0
P3	<0.001	-21.7	1.60
P6	#N/A	-1.61	-
P9	<0.001	-4.73	0.34

Figure 5.20: Significance level and numerical parameter values of production time t as explanatory variable in univariate logistic models describing occurrence of PD and ISA at time t given PD or ISA actually occurs for each of the production areas.

By inserting the above variable parameters into Equation 13 and 14, we have the following univariate logistic models that describe the PD and ISA occurrence at a specific time t during production given PD or ISA occurs. Except for P6, where a constant probability is used

$$P^{P3}_{t|PD} = \frac{1}{1 + e^{-(-5.71+0.54t)}}. \tag{23}$$

$$P^{P6}_{t|PD} = \frac{1}{1 + e^{-(-3.99-0.42t)}}. \tag{24}$$

$$P^{P3}_{t|ISA} = \frac{1}{1 + e^{-(-21.7+1.60t)}}. \tag{25}$$

$$P^{P6}_{t|ISA} = \frac{1}{1 + e^{-(-1.61)}} = 0.167. \tag{26}$$

$$P^{P9}_{t|ISA} = \frac{1}{1 + e^{-(-4.73+0.339t)}}. \tag{27}$$

5.2 Estimation VB-growth function coefficients

Weight development of salmon is described with VB-growth function in our proposed model. The equation below is the deterministic VB-growth function which is the same as presented in Section 3.1.

$$w(t) = w_\infty(a - be^{-ct})^3. \tag{28}$$

As mentioned earlier, w_∞ describes the maximum weight of salmon. In our proposed model, this parameter for each production area has been set equal to the maximum observed salmon weight in the production data from each production area. VB-growth function is nonlinear and estimation of coefficients a, b and c requires nonlinear approach. The following table presents the numerical values of the estimated coefficients which we obtained through generalized reduced gradient (GRG) nonlinear least-squares regression using the Microsoft (MS) solver function.

	P3	P6	P9
W_∞	8276	7114	7235
a	1.11	1.25	1.22
b	0.93	1.09	1.06
c	0.066	0.060	0.053

Figure 5.21: Estimated parameters in the von Bertalanffy growth function.

Regression was performed on average weight per salmon fish which is on a monthly basis and the variable t represent, hence, time in month since production start. With the above coefficients, we use VB-growth function to simulate average weight per fish at time t.

5.3 Estimation of proven yield weight

Proven yield is calculated as the average weight of the recent harvested salmon under normal circumstances. With normal circumstances we mean production cycles which are not infected by either PD or ISA, in other words healthy production cycles. Proven yield weight for each production area is thus equivalent to the mean of harvested average weight of healthy production cycles in each production area. The following figure re present the numerical values from Section 4.2.3.

	P3	P6	P9
Proven yield weight per fish (kg)	4.51	4.72	4.09

Figure 5.22: Proven yield weight.

The values in Figure 5.22 can be found in both Figures 4.7 and 4.8 for healthy production cycles.

6 Results

In this section, we present the simulated results from the BIP-model. The premiums are calculated on a regional level, and can, therefore, be viewed as the average insurance premium for the given region. We will first present the insurance premiums for our base case with a fixed loading factor γ and the insurance fraction h, for each production area and for the multiple location contract that is bundled with one average farmer from each of the production areas. Based on these premiums we calculate the diversification effect of the multiple location contract with Equation 10 in Section 3. In addition, all of the premiums and the diversification effect are evaluated on two different PD-policy regimes: one regime where the authority strictly enforces the PD-policy that we name *PD restricted*, and one regime where the authority never enforces the PD-policy that we name *PD relaxed*. Thereafter, we present a sensitivity analysis of the premiums on the loading factor γ, and insurance fraction h. Then we will present the simulated risk characteristics, and finally, discuss the results.

6.1 Simulated insurance premiums for base case

Figure 6.23 shows the simulated premiums in million NOK and percentage of the proven yield value[4] for each region as well as for a multiple location contract that is a bundle of one location from each production area. The premiums are presented for both policy regimes, as mentioned above. The simulations are conducted on our base case with an insurance fraction equal to 75% ($h = 0.75$), loading factor equal to zero ($\gamma = 0$), an initial stock size equal to 100.000 fish, an agreed upon price per kg fish of 60 NOK and a risk free interest rate of 2%. The multiple location contract has, therefore, an initial stock size of 300.000 fish.

	Single location P3		Single location P6		Single location P9		Multiple locations		Diversification effect	
	PD restricted	PD relaxed	PD restricted	PD relaxed	PD restricted	PD relaxed	PD restricted	PD relaxed	PD restricted	PD relaxed
Insurance Premium in million NOK	9.9	6.3	8.9	5.0	5.0	5.2	16.2	8.7	-7.6 (-32%)	-7.8(-47%)
% Proven yield value	38 %	24 %	33 %	19 %	22 %	22 %	22 %	12 %		

Figure 6.23: Simulated insurance premiums for single location and multiple location model.

The results in Figure 6.23 shows that P3 and P6 is highly sensitive to changes in PD-regimes, with respectively 36% and 44% reduction in premium from PD restricted regime to PD relaxed regime. P9, however, is almost indifferent between the two regimes. Another interesting result from Figure 6.23 is differences in premiums between the regions. In the PD restricted regime, the premium in P3 is about twice as high as in P9. However, when the policy is relaxed, the differences nearly zeros out. Next, the results show that the diversification effect of having multiple location contract that consists of one location from each production area rather than three individual contracts gives a 32% and 47% reduction in the premiums for PD restricted and PD relaxed regimes respectively.

6.2 Sensitivity analysis

Both insurance fraction h and loading factor γ are two essential components in our proposed BIP model. As mentioned earlier, insurance fraction is a number between 0 and 1 which dictates the amount of proven yield a farmer insures. For example, when h equals 0.5, the farmer only insures half of the average of his recent harvested salmon biomass. In the following sensitivity analysis of insurance fraction, we show how simulated insurance premium as a percentage of the proven yield value change when h varies between 0.55 and 0.85. Also, as mentioned earlier loading factor γ reflects a risk premium that compensates the insurer for taking on non-diversifiable risk, plus additional insurance transaction costs for writing the insurance contract. When conducting a sensitivity analysis on γ, we show how different loading factors affect the simulated insurance premium as a percentage of biological asset value.

6.2.1 Sensitivity analysis of the insurance fraction h

Figure 6.24 and 6.25 display simulated insurance premium values for different insurance fractions for both single location and multiple location model. The left figure simulates the premiums under PD restricted policy regime, and the right figure simulates the premium under PD relaxed policy regime.

[4]The value of the expected harvested biomass based on historical data

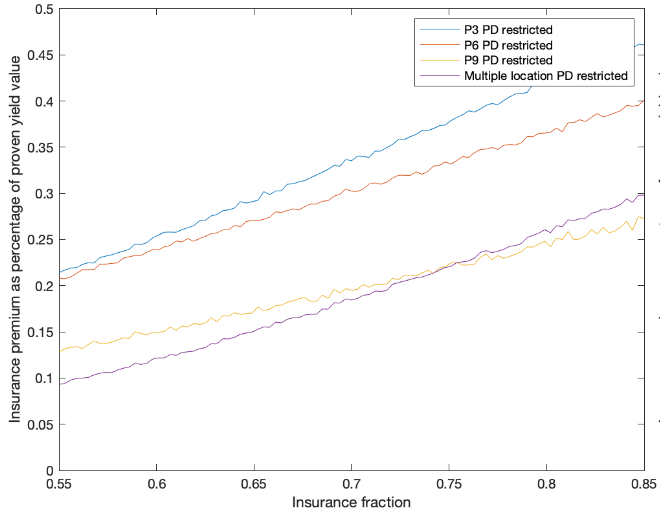


Figure 6.24: Sensitivity analysis of insurance fraction under PD restricted policy.

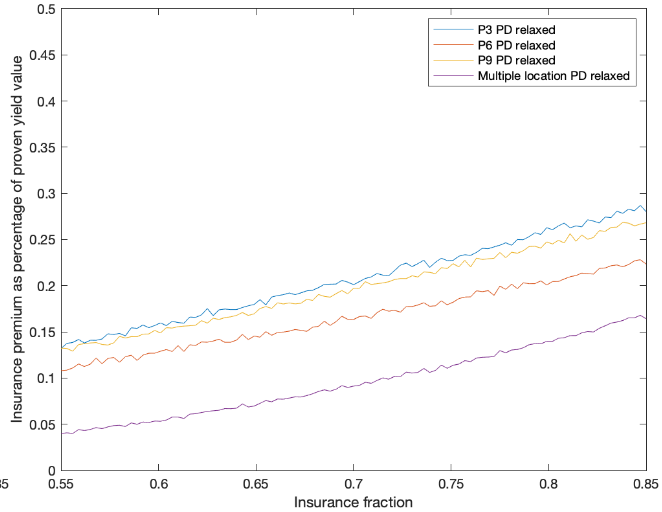


Figure 6.25: Sensitivity analysis of insurance fraction under PD relaxed policy regime.

A common feature for the above figures is the increase in premiums as insurance fraction increases. This happens regardless of the production area and whether locations are pooled or not, and can be explained intuitively as follows. As insurance fraction increases, the farmer is insuring more of his biomass. Therefore, it demands less decrease in realized harvested biomass from the expected harvested biomass to trigger an insurance payout. In other words, a higher insurance fraction results in more frequent and higher magnitude of insurance payouts, and the premium, hence, increases.

Figure 6.24 shows that the insurance premium for P3 and P6 increase faster than the premium to P9 when the insurance fraction increases. One possible explanation behind this phenomena is the difference in severeness of PD outbreak between P3, P6, and P9. As mentioned earlier, PD outbreak is recorded in a large portion of production cycles in P3 and P6 where P3 is most severe with 60% of its production cycles infected by PD versus 40% in P6 and none in P9. As insurance fraction increases, a more substantial portion of early harvest risk due to PD is included in the biomass insurance for locations in P3 compared to locations in P6 and P9. This more substantial increase in early harvest risk results in a larger increase of the likelihood for an insurance payout and thus a steeper increase of the insurance premium. Figure 6.24 also shows that the insurance premium for the multiple location contract increases less steeply than the premium for P3 and P6 but more steeply than P9. This can be explained with the diversification effects where an increased early harvest risk due to PD in P3 and P6 are partly being compensated by the no PD risk in P9. This results in a smaller increase in likelihood for an insurance payout and thus less steep increase in insurance premium. Figure 6.25 shows that insurance premiums for P3 and P6 go down when the risk of early harvest due to PD is removed (PD relaxed). This observation is expected since removing one risk of harvesting the biomass early results in a reduced likelihood of triggering insurance payout and thus less insurance premium. The slope of insurances premium for the production areas and multiple location contract are still positive which is due to the fact that there still are other early harvest risks in play and increasing the insurance fraction results in a larger portion of these risks being included in the biomass insurance and thus resulting increased likelihood of an insurance payout.

6.2.2 Sensitivity analysis of loading factor γ

Loading factor γ is a component which has been set equal to zero in our base case for the insurance contracts to the individual production areas and on the multiple location contract. This factor compensates the insurance company for taking on undiversifiable risk by increasing the insurance premiums with a multiple of γ. The loading factor is also used to cover the administration- and operational-cost of providing biomass insurance. The loading factor is, therefore, usually above zero. The following two figures display how insurance premiums change with various loading factor γ given insurance fraction at 65% and 75%. Figure 6.26 shows outputted insurance premiums for the production area, and Figure 6.27 presents simulated results for the multiple location contract.

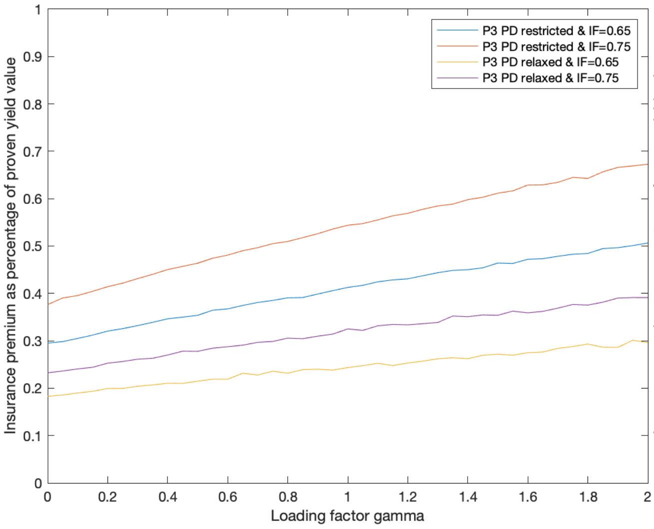


Figure 6.26: Sensitivity analysis of loading factor γ for P3 both under both PD restricted - and PD relaxed - policy regime.

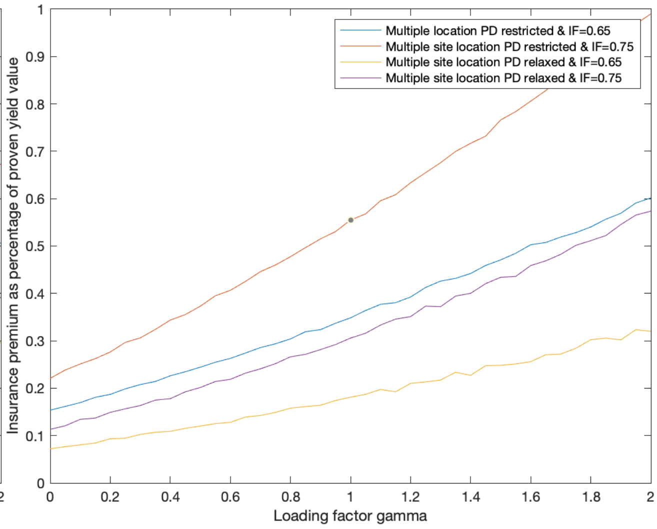


Figure 6.27: Sensitivity analysis of loading factor γ for multiple location contract under both PD restricted - and PD relaxed - policy regime.

According to the proposed insurance model, Equation 5, the loading factor is affecting the insurance premium exponentially with the factor of $(1+\gamma)^t$, where t denotes time. As we would expect, both figures show that insurance premiums increase with higher γ regardless of insurance fraction. Figure 6.26 and Figure 6.27 shows that the insurance premium curve with higher insurance fraction lies higher regardless of loading factor γ. As mentioned in Section 6.2.1, a higher insurance fraction results in a higher probability of insurance payout, regardless of the value of the loading factor γ. In addition Figure 6.26 and 6.27 show that the insurance premium increases slightly faster when insurance fraction is higher. In other words, insurance contracts with higher insurance fractions h are more sensitive to the loading factor γ.

6.3 Simulated risk characteristics

Figure 6.28 shows the share of simulated weeks that are over the sea lice limit and share of simulated production weeks with PD and ISA. P3 has 14% simulated weeks over the sea lice limit, which is near twice as many as in P6 and P9 with 8%. Compared to the share of production weeks over the sea lice limit in our data sample in which is illustrated in Figure 4.3, the simulations overestimate the shares with a factor of about two. However, the simulations match the relative differences in the shares between the regions. Next, P3 has substantially more production cycles with PD with a share of 72% compared to 41% and 0% for P6 and P9. Compared to the share of PD cycles in our data sample, this matches reasonably well in both the share values and the relative differences in the shares between the regions. The same goes for the share of production cycles with ISA.

	P3 PD restricted	P3 PD relaxed	P6 PD restricted	P6 PD relaxed	P9 PD restricted	P9 PD relaxed
Share of production weeks over sea lice limit	14%		8%		8%	
Share of cycles with PD	72 %		41 %		0 %	
Share of cycles with ILA	2 %		2 %		17 %	
Harvested average weight per fish (kg)	1.84	3.05	2.75	3.98	3.29	3.22
5% Percentile of biomass dist. (kg/fish)	0.23	0.23	0.16	0.27	0.22	0.22
10% Percentile of biomass dist. (kg/fish)	0.37	0.37	0.27	0.42	0.48	0.48
20% Percentile of biomass dist. (kg/fish)	0.55	0.75	0.60	1.06	0.83	0.83
30% Percentile of biomass dist. (kg/fish)	0.99	1.25	0.82	1.93	1.51	1.51
40% Percentile of biomass dist. (kg/fish)	1.25	2.15	1.06	3.32	2.04	2.04
50% Percentile of biomass dist. (kg/fish)	1.53	2.81	1.62	5.14	3.20	3.20

Figure 6.28: Statistics of simulated risk characteristics of adult female sea lice, PD and ISA disease. In addition mean and percentiles of harvested average weight per fish from 5% to 50%.

Next, Figure 6.28 also shows the simulated average weight and quantiles of harvested fish per production area for both PD-policy regimes. The results show that the average weight of harvested fish in P3 and P6 dramatically decreases from respectively 3.05kg and 3.98kg in PD relaxed regime to 1.84kg and 2.75kg in PD restricted regime. By taking a closer look at the quantiles, we see that the PD-policies regimes start to affect the 20% lever for P3, and at the 10% level for P6. P9 is as expected indifferent between the two regimes at both the average weight and all the quantiles. Furthermore, the simulations underestimate the average harvest weight regardless of policy regimes when comparing to the average weight from our data sample that is used to calculate the proven yields in Section 5.3.

6.4 Discussion

The simulated premiums in Section 6.1 are relatively high, with up to 38% of the value of proven yield at P3 under the PD-restricted policy. Some of these premiums are likely overestimated, which could be explained by two factors. First, as we saw in Section 6.28 the sea lice risk seem to be overestimated when comparing to the share of production weeks over the sea lice level with the historical data. As mentioned earlier, sea lice are part of the early harvest risk, and by overestimating this risk, the premium will increase, everything thing else equal. As mentioned in Section 4, one of the key characteristics of sea lice development is its path dependence. In this paper, we modeled the path dependence by using a regime shift model and historical simulation. However, every draw in a historical simulation is independent, and our model might, therefore, not model the path dependence to a sufficient degree. Second, the considerable difference in average weight between the simulations and sample date could suggest that the authorities do not strictly enforce their policies. In our simulations, we have forced the farmers to harvest every time they have three consecutive production weeks over the sea lice limit, at every ISA detection, and at every PD detection in the PD restricted policy regime. In reality, however, the authorities have the right to force harvest upon these measures, but not the obligation. Our findings in Section 4 suggests that the authorities do not enforce the PD policy strictly. In addition, by relaxing the PD-policy, the simulated average harvest weight is still lower than the average harvest weight from the sample data, which could indicate that the authorities are not strictly following their sea lice and ISA policies.

The premiums sensitivity to the PD policy regimes indicates that there exists a considerable political risk with regards to PD in P3 and P6. Even though the regulators up til now have likely not strictly enforced their policies, however, this practice can change during a production cycle. Thus, the insurance companies have to take into account this political risk when providing biomass insurance. As mentioned in Section 1, a factor which has been pointed out as challenging for insurance writers is the constant and rapid change of the aquaculture industry. In light of the lack of risk management tools obtainable for small- to medium-sized farmers and the importance of these farmers to the municipalities, the authorities should have an incentive to facilitate the biomass insurance marked. Our results indicate that a change in how a policy is practiced, from not enforcing harvest on PD to enforcing, leads to increased insurance premium which suggests there is risk associated with changes in policies. Therefore, to facilitate the biomass insurance market, the authority can prohibit sudden changes in policies and how they are practiced. The policies themselves are not critical, but the risk of sudden changes are. If the insurance writers do not have any promises of consistent enforcement of policies, they have to also price risk of regulatory changes into the premiums resulting a higher premium, and biomass insurance will become a less attractive risk management tool. The analysis of the sensitivity of the premium with different PD-policy regimes illustrates that our model can be used for other purposes than to price biomass insurances. Since our BIP-model are based on a simulated harvest distribution, it can also be used to analyze how different policies will affect farmers in various regions and the industry as a whole. For example, we have shown that the PD-policy can have a dramatic impact on the farmers in P3 and P6 if strictly enforces, but no impact on P9. In order for the authorities to develop successful policies that fulfill their purposes, our model can be used to analyze how different alternatives affects the farmers.

Next, our results show diversification effect by pooling multiple locations in one contract. Compared to having several individual contracts, it greatly reduces the premium. Despite this contract triggers insurance payout less frequently, it still gives the farmer a more economical hedge against the most critical scenarios. Therefore, it is a more attractive risk management tool for some farmers than others. Our results show that the diversification effect has a considerable impact on the premium by pooling as few as three locations together, this product can hence also be available for small- to medium-sized farmers. Also, this result nicely illustrates the benefits of spatial diversification within the aquaculture industry. The magnitude of the premiums reduction in our results can be used as an argument to consolidating small farms from a risk management perspective.

7 Conclusion

In this paper we have conducted a brief investigation on the risk management practices among the listed aquaculture companies on Oslo Stock Exchange, performed an empirical analysis of the sea lice-, PD-, ISA-, mortality- and weight-development at three production areas in Norway, and developed a stochastic biomass insurance pricing (BIP) model. The findings from the investigation of the risk management practices indicate that there is an underutilization of biomass insurance and other risk management tools such as spatial diversification and technology investment are mainly available to the largest farmers. However, we argue that biomass insurance should be an attractive risk management tool, especially for small- to medium-sized farmers due to its scalability and ability to hedge against the farmers' tail risk. The recent algal bloom in Norway illustrates how vulnerable smaller farmers are to biological shocks and how dependent the municipalities has become of the farmers' existence, which should give the authorities an incentive to facilitate the biomass insurance marked.

From the empirical analysis, we find considerable differences in the risk characteristics between the production areas. Production area 3 (P3) is much more susceptible to sea lice and PD than production areas 6 (P6) and 9 (P9). P9, on the other hand, is much more susceptible to ISA than the other production areas. From a risk management point of view, this is interesting due to the fact that regulation which is aimed at a specific biological problem will impact different production areas differently. For example, a stricter sea lice regulation will have a greater negative impact on P3 than the others. Therefore, in order to reduce the political risk, the farmer should spatially diversify its production. Next, we find regime shifts for the change of sea lice level based on the sea lice level itself. This is likely caused by the farmers' sea lice treatment strategies. Since sea lice treatments often cause small jumps in the mortality, the farmers are likely to not conduct any sea lice treatment at low sea lice levels. However, as soon as the sea lice level approaches the upper threshold set by the authorities, some of the farmers initiate sea lice treatments to prevent the sea lice level from breaching the threshold. When the sea lice level exceeds the sea lice threshold, the authorities can force the farmer to conduct an early harvest. As an early harvest has a greater negative impact on the revenue than a small jump in the mortality, nearly all of the farmers conduct sea lice treatments. We have also found regime shifts in the mortality rate based on the production time, which could be explained by two factors. First, post-smolt mortality rates are expected to be high in the first couple of months due to the smolt adjusting to new ocean climate, interspecific competition, and intraspecific interactions. Second, it is reasonable to assume that the sea lice treatment activity increases with production time due to the rising sea lice level. Since sea lice treatments often lead to small jumps in the mortality, the mortality rate is often high towards the end of the production cycle. Furthermore, our logistic regression on ISA confirms Lyngstad et al. (2018) finding of latitude as an explanatory variable.

The simulated tail risk from our BIP-model matches reasonably well to the tail risk of the sample data, except that the BIP-model seems to overestimate the sea lice risk. The sea lice risk is likely overestimated due to insufficient modeling of the path dependency of the sea lice development. Despite the reasonable match in tail risk, the average harvest weight from the simulations is considerably lower than the average harvest from the sample data. One explanation for this difference could be that the authorities are not strictly enforcing their policies. In our simulations, we have forced the farmers to harvest every time they have three consecutive production weeks over the sea lice limit, at every ISA detection, and at every PD detection in the PD restricted policy regime. In reality, however, the authorities have the right to force harvest upon these measures, but not the obligation. Some of our findings in the empirical analysis indicate that the authorities are not strictly enforcing the PD-policy. By relaxing the PD-policy to never force an early harvest, the premiums in P3 and P6 decrease greatly, and the average harvest weight increase substantially. This result might suggests that the authorities are not strictly enforcing the sea lice and/or ISA policy. Because, with restricted PD policy, the simulated realized biomass becomes significantly lower than what the farmer harvests on average. Due to the fact that the authority is not strictly enforcing the regulations, the simulated insurance premiums in our paper are likely overestimated compared to their fair value. Even though the authorities are not strictly enforcing their policies today, but the fact that they have the right to do so induces a substantial political risk that the insurance writers have to price into the contracts. Therefore, if the authorities wish to facilitate biomass insurance marked, they should limit the uncertainty of how policy are enforced.

We find that the diversification effect of pooling multiple locations in one contract decreases the premium substantially. Our results suggest that it is possible to decrease the premium as much as 47% by only pooling three locations in one contract, and is, therefore, also obtainable and attractive for small farmers. This result also illustrates the magnitude of the benefit of spatial diversification in the aquaculture industry, which can be used as an argument for consolidating smaller farms from a risk management perspective.

An interesting property of our BIP-model is that it can be used for other purposes than to price biomass insurance contracts. The BIP-model is based on simulating the harvest distribution that takes into account the early harvest risk due to policies on sea lice, ISA, and PD. Hence, it can be used to evaluate how different policies are affecting farmers located in different regions. Thus, it can be applied by the authorities in their preparation for either adjusting or adding new policies. Also, if any farmers or investors want to reduce the political risk by spatially diversifying their production, they can use the model to analyze different regions sensitivity to different policies.

In what follows, we propose several suggestions for future research. First, it would be interesting to investigate further on how to model the path dependency of sea lice development. This would be beneficial to not only increase the accuracy of our BIP-model but could also be used in cost of sea lice and sea lice treatment models. Next, an interesting extension of our BIP-model would be to explicitly model sudden spikes in the mortality. In this paper, we have used a historical simulation approach, which is appropriate to model risks that have happened in the past. However, for certain regions, where rare biological shocks, such as algal bloom, have not occurred in the past, the historical simulation approach might underestimate the risk of sudden spikes in the mortality. Finally, it would be interesting to investigate how to determine the loading factor γ, which is a function of operational- and administration-cost of providing biomass insurance, and the non-diversifiable risk the insurance writers take on.

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