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Company level biodiversity impact assessment: An application to the aquaculture industry in Norway

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ABSTRACT

This paper proposes a company-level biodiversity impact assessment framework tailored to the aquaculture industry. Using publicly available data from Norway, we analyze the relative biodiversity performance of companies based on the following impact variables: sea lice, escapes, diseases, bottom conditions, and lice treatments. We apply an unsupervised clustering methodology to classify and rank companies based on their aggregated biodiversity impact over time. Our findings suggest that companies operating in the northern production areas of Norway have a geographical advantage due to lower sea temperature and lower density of localities, resulting in higher biodiversity rankings. When considering the biodiversity ranking within regions with comparable biological conditions, we find that larger and publicly traded salmon farming companies perform better than smaller privately owned ones, potentially indicating better managerial practices related to biodiversity issues.

1. Introduction

With the current dramatic extinction rate of species, the erosion of biodiversity poses a considerable risk to our society's sustainable development [3,8]. Under these circumstances, substantial investments are required each year to reverse the decline in biodiversity [41]. This makes businesses and the financial sector key players in achieving transformations to address biodiversity loss due to their ability to divert funds to sustainable projects through investment decisions [6,45].

Nevertheless, until recently, the efforts to integrate ESG (Environmental, Social, and Governance) factors into business and investment processes have not demonstrated a significant focus on biodiversity impacts [16]. With the establishment of the United Nations (UN) Sustainable Development Goals (SDGs) in 2015 and recent regulatory initiatives, such as the EU's Sustainable Finance Action Plan (SFAP) and the Sustainable Finance Disclosure Regulation (SFDR), more focus is being placed on improving sustainability and biodiversity disclosure. Among other important initiatives are the development of sustainability disclosure standards by the International Sustainability Standards Board and the establishment of the Taskforce on Nature-related Financial Disclosures.[1] However, market participants that are looking to invest in individual companies currently still lack suitable tools and methodologies to integrate biodiversity considerations into their decision-making processes.

In this paper, we develop a methodology to measure and compare biodiversity impact performance of Norwegian salmon farming companies. As fisheries are reaching their limits in satisfying a growing demand for high-quality marine proteins, the aquaculture industry has great potential to satisfy the need for expansion in seafood production, while at the same time helping to achieve several of the UN's SDGs [1,22,23]. The opportunities for expansion are, however, limited due to environmental challenges that the industry is facing today. In Norway, the salmon farming industry has grown from a niche market to a massive industrial adventure, as half of the world's salmon supply in 2021 (over 1,5 million tonnes of Atlantic salmon) was produced in Norway [9]. As production has grown, the environmental and biodiversity impact of the industry has also increased due negative pressure on marine biodiversity, including wild salmon, non-target crustaceans, and various seabed invertebrates through disease outbreaks, escapes from fish farms and sea lice infestations, as well as adverse effects on the coastal fisheries and the sea floor due to environmental pollution [11,29,43].

In light of these challenges, it is crucial to redirect capital flows toward more sustainable aquaculture companies. However, to do so, capital providers and financial institutions must be able to distinguish

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[1] https://www.ifrs.org/groups/international-sustainability-standards-board/, https://tnfd.global/.

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which companies are actually more sustainable. Consequently, there is a need for a methodology to compare aquaculture companies based on their biodiversity footprint. Despite recent focus of capital providers on sustainability, there currently exists no standardized framework that enables such assessments. While data on company-level ESG factors is readily available, it lacks nuance related to specifics of the aquaculture industry. At the same time, despite a sizeable literature on environmental and biodiversity issues within the aquaculture industry as a whole [10,21,29,32], there is still a clear lack of studies that attempt to measure and identify company-level sustainability impacts and performance. In this paper, we fill this gap in the literature by developing an assessment tool that allows to compare individual Norwegian salmon farming companies based on their biodiversity impact during the marine growth phase of salmon when the most dynamic interactions with marine wildlife occur. We utilize publicly available data in order to develop indicators based on the most important biodiversity impact variables identified in the literature, including lice counts, escapes, diseases, lice treatments, and bottom condition surveys [12,14,19,32,42]. Then we utilize an unsupervised clustering methodology to rank companies based on their biodiversity impact performance. First, we employ this methodology nationwide, comparing all the companies in our sample on all the five biodiversity impact indicators. The results from our model demonstrate a strong correlation between a company's biodiversity impact performance and geographical location, suggesting that companies operating in the southern and western regions of Norway perform have a greater negative impact on biodiversity than those operating in the northern region. This is likely due to the higher density of aquaculture operations in the fjords of the southern and western regions and the warmer average sea temperatures, which facilitate the spread of sea lice and diseases [13,30]. Our results also allow us to examine whether the biodiversity impact varies with firm size. Note that the structural diversity of Norwegian aquaculture industry with respect to firm organization provides a suitable setting to explore this hypothesis. Interestingly, our results show that large publicly listed companies get a lower overall ranking compared to several smaller privately owned companies when compared nationwide. This is related to the fact that large companies are more geographically diversified and, thus, operate in areas of high biodiversity pressure. This implies that they receive lower overall scores compared to the smaller companies operating solely in the northern regions with better biological conditions.

Next, we split the data set between companies operating in southwestern and northern areas of Norway and use our clustering methodology to create separate rankings for these two sub-samples. This allows us to compare companies operating under similar biological conditions in terms of temperature and locality density. Thus, the differences in the ranking of companies are likely to stem from managerial practices related to biodiversity. Our results show that large publicly listed salmon farming companies perform slightly better than smaller private companies in both regions. Potential explanations of the observed differences between private and publicly listed companies could be that the large listed salmon farmers focus more on sustainability and transparency to attract investors and have better routines due to a more extensive base of experience and resources.

In addition, we investigate which indicators have the greatest impact on the overall clustering score. This provides companies with insights into which factors they should focus on improving in order to increase their overall ranking relative to their peers. Our results show that improving a company's cluster placement on sea lice numbers and bottom survey scores has the greatest influence on its overall biodiversity impact performance score in both the southwestern and northern areas of Norway. Additionally, lice treatment methods have a significant impact on biodiversity scores in the southwestern areas of Norway, while diseases have a significant impact in the northern areas.

Our finding that biodiversity impacts vary across companies highlights the role of firm level actions in overall sustainability efforts. Nevertheless, while individual firms have the potential and responsibility to enact positive change, addressing biodiversity's broader challenges often require an ecosystem-wide perspective [38]. Hence, it is important to note that many challenges related to biodiversity are more effectively addressed through coordinated actions at higher governance levels, such as regulatory initiatives. For example, [37] illustrates that the firms lack have private incentive to reduce the number of escapees, suggesting that regulatory interventions are crucial. Ecolabels are another way to address this challenge as they provide an incentive for firms to tackles environmental issues for which they lack private incentives to act upon. Here, the difference between aquaculture and fisheries is important. In fisheries, ecolabels are granted at the broader industry level, while in the aquaculture industry, they are awarded at the firm or even location level. This suggests that ecolabels provide stronger incentives for aquaculture companies to implement sustainable practices at the firm level.

2. Material and Methods

2.1. Literature review

Impact investments and biodiversity impact assessments have received increased attention in ESG, sustainable finance, and responsible investments studies. Some studies have investigated the connection between biodiversity and finance, and why it is important for the finance industry to invest in biodiversity [34,40]. In the context of aquaculture, sustainability reporting has become increasingly important for the large salmon companies [28]. Several studies have also focused on how to develop and define biodiversity impact indicators to be used by company managers, investors and financial institutions [5,36]. These studies emphasize that there is a lack of indicators that measure company-level biodiversity impacts that could help to better assess corporate biodiversity performance. Several prominent organizations (for example, such as WWF, One Planet Program on Sustainable Food Systems, Finance for Biodiversity Foundation) identify and describe different tools that have been developed to assess the biodiversity impacts from a portfolio perspective. These tools apply mainly footprint approaches, which use various data sources, including corporate disclosures, estimated data, and third-party databases, to calculate the relevant impacts for the chosen ESG, SDG, or biodiversity variables involved. However, the disadvantage of footprint approaches is that they generally only capture a snapshot in time and thus can be challenging to use to support forward-looking risk assessment or impact monitoring. Our methodology addresses this challenge by measuring the biodiversity impact of salmon farming companies over several years. A large body of research within biodiversity impact assessments also focuses on frameworks and indicators for a specific industry, project, or area [4]. However, to the best of our knowledge, no studies have developed biodiversity impact indicators specific to the salmon aquaculture industry. The closest biodiversity impact assessment to ours is Protein Producer Index created by the FAIRR Initiative[2] that assesses the largest animal protein producers on critical ESG issues. Some of the variables included in this index are similar to the ones used in this study. However, the primary data sources for these variables are company disclosures. In this study, we use data provided by regulatory authorities rather than those provided by individual companies. This way, we avoid several issues related to data quality, transparency, and the lack of standardization.

To develop biodiversity impact indicators for salmon farming companies, we follow two criteria [4]: relevance and effectiveness. Relevance of indicators encompasses sensitivity and quantitative reference values, thereby allowing the selection of potential indicators. Effectiveness is the ability of the indicator to reach its predefined targets based on optimal data collection protocols. We choose to focus on escapes of farmed salmon, the effect of sea lice, diseases, medicinal usage

[2] https://www.fairr.org/index

concerning delousing treatments, and environmental impacts on the seabed in line with the literature studying biodiversity impacts of farmed salmon [10–12,14,15,21,29,32,42]. These studies, however, typically focus on the aquaculture industry as a whole rather than on how to separate the different companies in terms of environmental and biodiversity impact performance. Therefore, we add to the stream of literature on biodiversity impact assessment of the Norwegian fish farming industry by developing key biodiversity indicators and introducing a framework to measure and compare fish farming companies based on biodiversity performance.

2.2. Data description

We use publicly available data sets from the Directorate of Fisheries and the Norwegian Food Safety Authority. Around 90 companies produce the total supply of salmon in Norway, with 23 of these producing about 80% of the farmed salmon and trout in Norway, indicating a significant consolidation within the industry. Note that this consolidation has historical roots: up until 1991, the industry was predominantly owner-operated. This changed dramatically post-1991 due to mergers and acquisitions, as well as the general growth of farm size, so that even smaller entities in the sector have grown significantly [2,20,33]. In this paper, we focus on the 36 largest salmon farming companies in Norway in terms of slaughter weight in 2020.[3] Table 1 summarizes the primary data sources for the variables we use throughout this paper and presents basic descriptive statistics for the variables.

As stated in Table 1, the escapes input metric is a rolling average over the number of escapees per locality per year for the three years prior. This is done partly because escaped salmon can affect biodiversity several years after it has escaped, and partly to mitigate some of the influence big singular escape events can have on the escape score. The input metric we use for lice counts is the average number of mature female sea lice per counting over a whole calendar year. Our input metric for lice treatments is the number of medicinal lice treatments, as they have been shown to have a greater negative impact on biodiversity compared to an alternative method of delousing, which is mechanical approaches [14].[4] For diseases input metric, we only consider Infectious salmon anemia (ISA) and Pancreatic disease (PD) outbreaks, as these are the only outbreaks made publicly available by the Norwegian Food Safety Authority.[5] [42] highlights that frequent viral disease outbreaks in Norwegian salmon farming suggests wild salmon and local sea trout are likely to be exposed to these pathogens, but the exact effects have not yet been established. Although impact of PD and ISA on the wild fish is unknown, their management at the company can serve as an indication of the quality of disease control. For instance, effective handling of these diseases suggests robust overall practices that likely extend to other pathogens. As our ultimate goal is to compare companies, it is reasonable to assume that when a company performs notably worse than its regional peers it may point to lower quality of management practices. The environmental impacts on the seabed in our assessment model are represented by the data from bottom condition survey scores. These surveys are mandatory for Norwegian fish farmers and are done according to Norwegian Standard document “NS-9410″,[6] where the output scores range from 1 to 4, where 1 is defined as “very good” and 4 is “very bad” in terms of environmental bottom condition impacts under the location. Our input metric here is the percentage of survey scores that were either 1 or 2 for each company for a given year.

In order to assign biodiversity impact performance to a specific company, it is necessary to map all localities to the salmon farming companies we focus on in this paper. In order to do so, we use the data from the Norwegian Aquaculture Registry, where all companies with fish farming activities in Norway are registered with their permits and localities. To identify which localities belong to the 36 companies in our study, we need to make several assumptions due to the structure of the data available. First, the Norwegian Aquaculture Registry shows a snapshot of the current state of the locality structure. We therefore extract data on the locality structure per January 1st for all relevant years, assuming that the Norwegian locality structure per January 1st is a good proxy for the rest of the year.[7] Second, some localities are operated as joint ventures, where there is no publicly available data on which salmon farming company has the primary responsibility for the operations. Hence, we use the data on the permits registered on each locality to determine which company has the main responsibility for the operations. In particular, we assume that if a company has more than 80% of the production permits on a locality, it is the main operating company, assigning the locality and all its biodiversity impact measures to the given company with a weight of 1. Concurrently, a fish farming company having less than 20% of a locality’s permits is not assigned any of the biodiversity impacts from that locality. For companies with a share of permits on a locality between 20% and 80%, we assign equal weights. Third, at any given time, between 30% and 40% of localities in Norway are fallowed [39]. We assume that over time, all companies have the same share of their locations fallowed. This assumption is plausible as all salmon farming companies have incentives to keep the fallowing periods as short as possible. At the same time, the regulators demand a minimum fallowing period for each generation of fish [26]. Thus, we assume that the companies keep their fallowing periods as short as legally possible to maximize profits.

The extensive data cleaning and variable selection processes leave us with a data set consisting of 36 companies and 287 294 observations from the five biodiversity impact variables.[8] Among these companies, six (16,7%) are publicly traded on the Oslo Stock Exchange or Euronext Growth, while the rest are privately owned. There is a significant variation in the size of these companies, where slaughter weights range from 3600 tonnes to 262000 tonnes, while the number of localities varies from 6 to 147. Sulefisk AS only slaughtered 1,4% of the amount that Mowi ASA slaughtered in 2020, with Mowi’s volumes coming from 25 times as many operating localities. There are also differences in the geographical distribution of companies, with the majority of companies operating exclusively in either northern or southern Norway, and only four companies conducting operations in both regions. In 2017, the government of Norway introduced a new measure to combat sea lice problem that allows growth in specific regions based on the “the traffic light system”. It divided the Norwegian coastline into 13 production areas based on their sea lice levels where in green regions, farmers are allowed to increase production by 6%, in yellow regions, they have to keep constant production, whereas in red regions, production has to be reduced by 6%.[9] In our final data set, only 5 companies operate in more than two production areas, and only 3 operate in more than three production areas.

[3] An overview of slaughter weight for all Norwegian fish farmers with more than six permits was provided by Kontali Analyse.

[4] [44] provides a more detailed overview of the impacts of different delousing methods.

[5] A wide range of other diseases was discovered in 2021, which caused increased mortality amongst Norwegian farmed salmon but lack publicly available data ([39]).

[6] The standard/document by the Institute of Marine Research specifies sampling frequency and method for measuring and assessing bottom impact from marine aquaculture facilities.

[7] As seen in Appendix A, the number of localities per company is relatively stable on a year-to-year basis. Hence, the deviations throughout the year have a negligible effect on our results.

[8] Table B.1 in Appendix B provides an overview of all companies in our data set.

[9] An overview of the 13 production areas in Norway can be found at https://www.hi.no/hi/nyheter/2020/februar/trafikklys.

Table 1
Definition and statistics of variables before normalizing.

Biodiversity impact variable	Source	Years	Proxy	Indicator on company level	Mean	Median	SD
Escapes	The Directorate of Fisheries	2016–2021	Number of escaped farmed salmon	Escaped individuals per locality, rolling average last three years	152,659	2290	408,498
Sea lice	The Norwegian Food Safety Authority	2016–2021	Weekly reported lice counts	Average number of lice per count	0100	0104	0081
Lice treatments	The Norwegian Food Safety Authority	2016–2021	Number of medicinal lice treatments	Number of medicinal lice treatments per locality	1273	0879	1752
Diseases	The Norwegian Food Safety Authority	2016–2021	Confirmed disease outbreaks (ISA and PD)	Annual outbreaks per locality	0258	0258	0247
Bottom conditions	The Directorate of Fisheries	2016–2021	Bottom survey scores	Percentage of bottom survey scores that are 1 or 2	88,123	89,237	12,275

2.3. Methodology

One of the challenges when creating a common rating methodology is the relative importance of the variables used. The assignment of weights to the different variables is subjective, as different metrics are of different importance to different stakeholders. To meet this challenge, we utilize the unsupervised K-means clustering algorithm as a vital part of our model, where assignment of weights to the input variables is not necessary. The intuition behind K-means clustering is to minimize the Euclidean distance between nodes in the same cluster and maximize the euclidean distance to nodes in other clusters.[10] This way, the final clusters can be used to identify nodes - in our case salmon farming companies - with similar biodiversity impact performance. Mathematically, the algorithm initializes k cluster centroids, $\mu_1, \mu_2, \mu_3, \dots, \mu_k \in \mathbb{R}^n$, and then the steps outlined in (1) are repeated until convergence.

$$\begin{aligned} \forall i \in \{1, m\} c^{(i)} \quad &:= \quad \underset{j}{\operatorname{argmin}} \left|\left|x^{(i)} - \mu_j\right|\right|^2, \\ \forall j \in \{1, k\} \mu_j \quad &:= \quad \frac{\sum_{i=1}^{m} \mathbb{1}_{c^{(i)}=j} x^{(i)}}{\sum_{i=1}^{m} \mathbb{1}_{c^{(i)}=j}} \end{aligned} \tag{1}$$

where $x^{(i)}$ denotes the i-th data point in the dataset, where m is the total number of data points, k is the number centroids, $c^{(i)}$ is a cluster label for each data point, and $\mathbb{1}$ is an indicator function.

For every year in our data from 2016 to 2021, we collect company performances on our five biodiversity impact variables: escapes, sea lice, diseases, lice treatments and bottom surveys. Each company is compared to its peers annually before its performance is scaled from 0 to 10. The best-in-class on each biodiversity metric gets a rating of 10, while the worst-in-class gets a 0. After that, the K-means clustering algorithm minimizes the distance between the biodiversity scores of the different fish farmers, aiming to place the most similar performing companies in the same cluster. Finally, we rank the clusters according to the average biodiversity scores of the companies within each cluster. An overview of our model is shown in Fig. 1 below.

The annual cluster distribution is then used to rank the companies over a longer time frame. In order to rank the best biodiversity impact performers over a six year period, we sum up the number of times a company ended up in different clusters as shown in Fig. 2. This way, if a company is in the best cluster all six years, it gets a score of 6. A lower score is better, meaning that the company achieving the lowest score in this part of the model is the overall best biodiversity performer. We use $k = 4$ for all clustering approaches in this paper since 4 is among the K's achieving the best silhouette scores. It also provides enough clusters to separate between companies while sufficient number of companies in each cluster. With $k = 4$, the best possible score is 6 - ending up in the best cluster, 1, all years. The worst possible score is 24, ending in the worst cluster, 4, all years from 2016 to 2021. The clusters may be classified according to their characteristics and the identification variables considered: .

- Cluster 1: “Top biodiversity impact performers”,
- Cluster 2: “High biodiversity impact performers”,
- Cluster 3: “Medium biodiversity impact performers”,
- Cluster 4: “Low biodiversity impact performers”.

3. Results and Discussion

3.1. Model results

To study the biodiversity footprint of aquaculture companies in Norway, we first perform a nationwide comparison between all the 36 salmon farming companies in our sample (described in Section 2.2). We run our model illustrated in Figs. 1 and 2, including all our five biodiversity impact variables in a multivariate clustering framework. Each company gets classified into a cluster yearly based on its biodiversity impact performances. Aggregating the cluster placement scores over the period from 2016 to 2021 results in the biodiversity impact ranking of each salmon farming company. Fig. 3 below illustrates the number of companies in each cluster over time. Cluster 1 - the best cluster - is the most populated, with approximately 40% of the companies on average, whereas Cluster 4 is the least populated, occasionally with as few as one or two companies.

The development over time of average cluster scores for the five variables, as well as the overall average score, is presented in Fig. 4. As can be seen, the average scores in Cluster 1 tend to be higher and are less volatile than in the other clusters. However, the companies in this cluster tend to perform worse on lice treatments and escapes, which indicates that these variables have a smaller effect on the overall score. It can also be seen that the companies in Cluster 4 tend to perform worse than those in the other clusters, especially based on bottom conditions and diseases. This is, however, not the case for lice counts. For this variable, the normalized scores in all clusters are generally lower than for the rest of the variables, even for Cluster 1 where the average score never exceeds 8, indicating that it is difficult to achieve high company scores on sea lice counts. Notably, the scores on escapes are large and relatively stable for all clusters, except Cluster 4. This is due to several large escape incidents in 2016 and 2017 that affect the normalized score to a large degree.

The cluster scores described in this section result in the overall ranking presented in Table 2. The full ranking table is presented in Appendix C.

Interestingly, the top ten operators have localities exclusively in the seven northernmost production areas, whereas the ten worst biodiversity impact performers have localities solely in the six southernmost production zones. Among the salmon farming companies in our data set, Mowi, Lerøy, Grieg and Salmar have the most diversified locality

[10] More information regrading K-means clustering approach can be found in [17]. Also see, e.g., [18,31,35] for applications of clustering to measure and categorize the companies' sustainability performance.

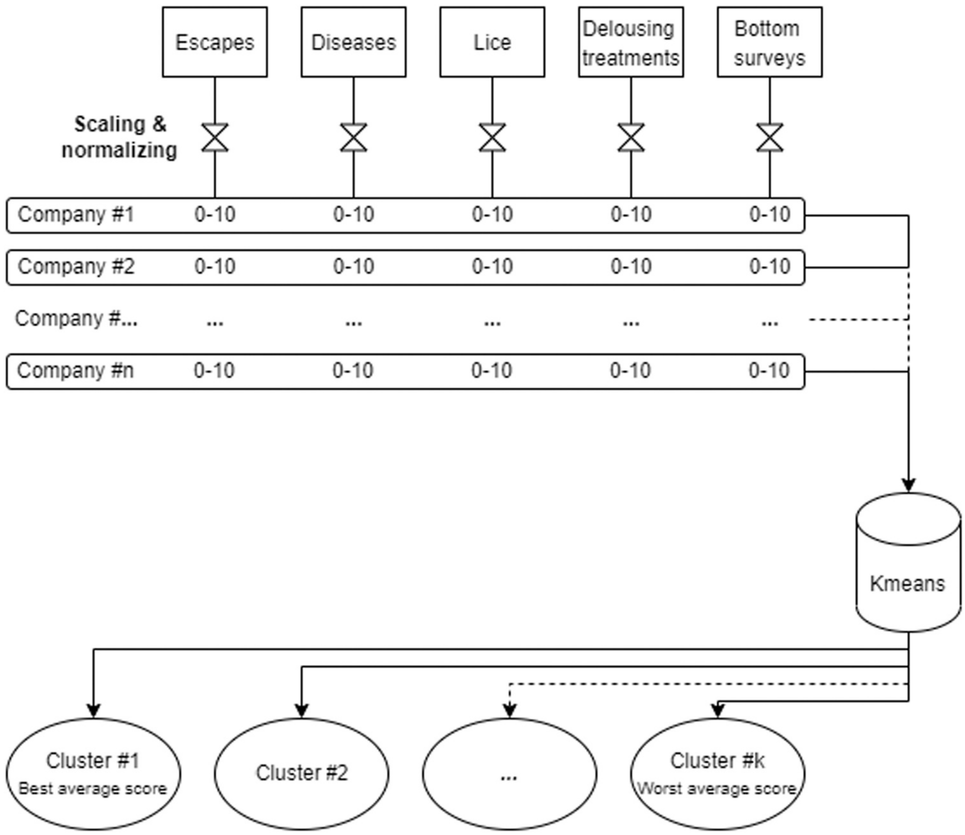

Fig. 1. Illustration of our application of the K-means algorithm.

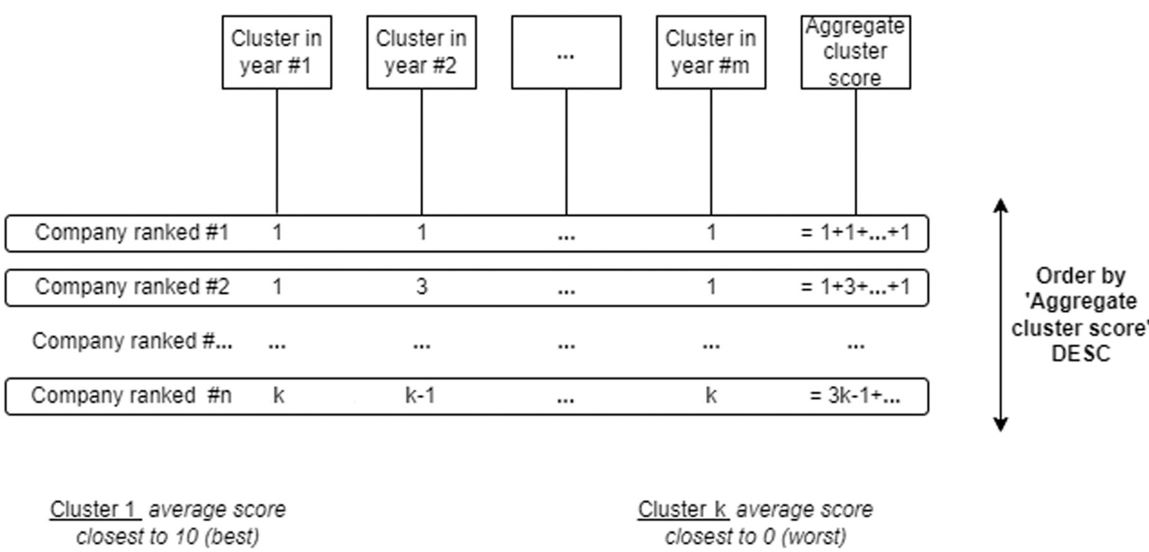

Fig. 2. Illustration of ranking procedure scoping m years. We aggregate a cluster score from all years and order the companies descending based on the aggregated biodiversity impact scores.

structures spread over several production zones in both north and south of Norway as shown in Table B.1. However, none of them are among the best performing companies in our ranking, unlike smaller privately owned companies. This can potentially be explained by their locality structure. The majority of smaller salmon farming companies operate in a limited geographic area of Norway, leaving them exposed to biodiversity impact risks out of management control. The conditions in terms of sea water temperature and locality density in the north are more favorable, leaving southern farmers exposed to higher risk of high sea lice levels and disease outbreaks[13,30]. For the diversified companies with localities in different part of the country, this effect is diluted, which explains why they do not stand out in the nationwide comparison.

In order to examine the contributions of individual input factors more closely, we run our model for each of our biodiversity impact variables separately. As a result, we get singular rankings for each biodiversity indicator. In Fig. 5, we present the cluster distributions resulting from these rankings where we highlight the share of companies in the clusters that operate in the southwestern areas or the northern

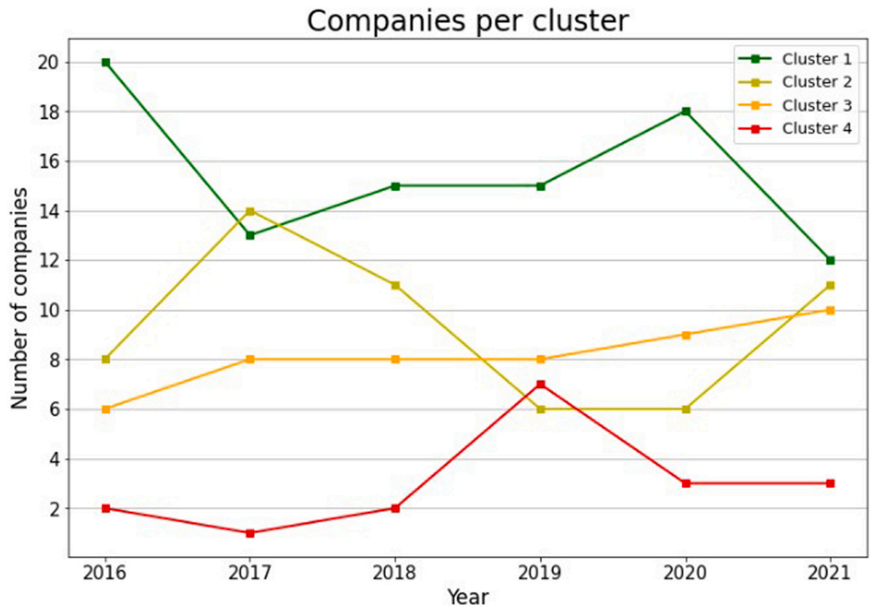

Fig. 3. Number of companies per cluster per year.

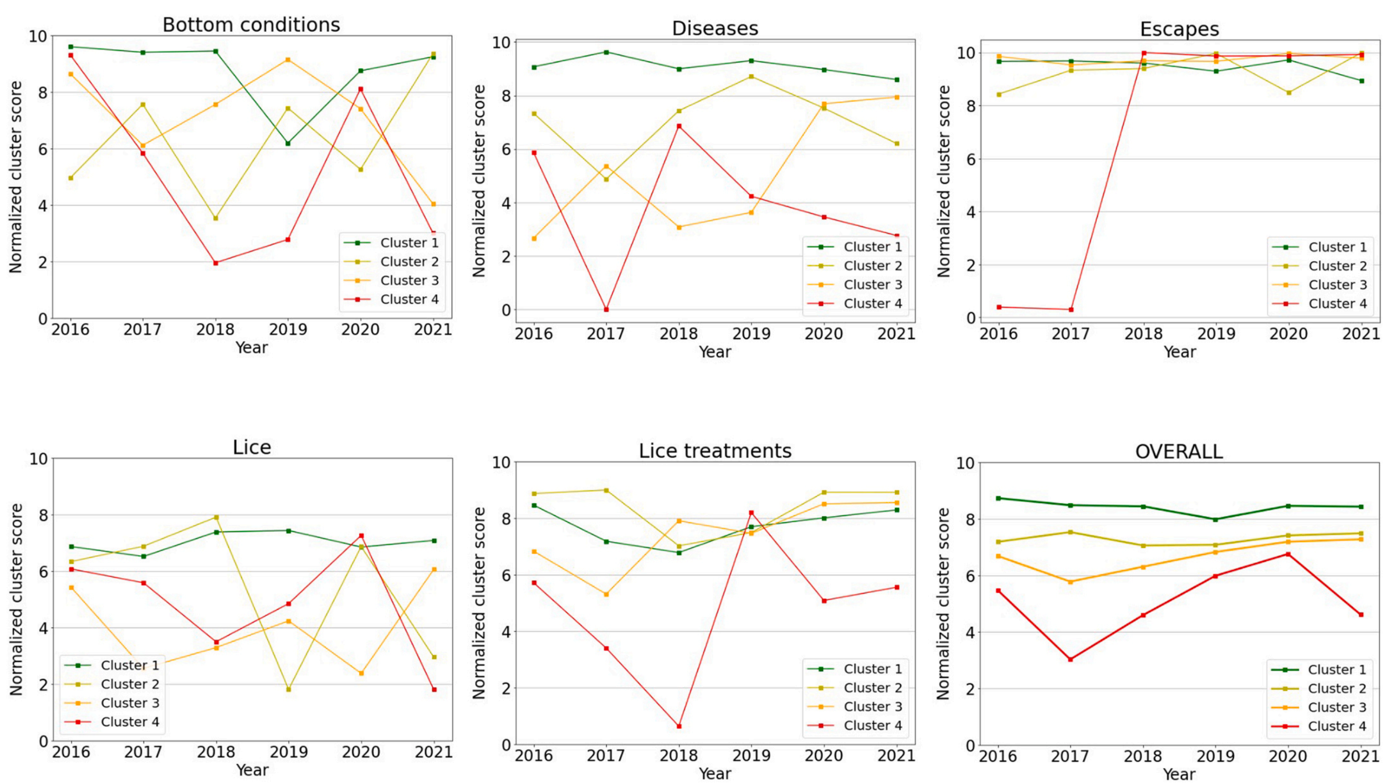

Fig. 4. Development of average cluster scores for the different variables from 2016 to 2021.

areas of Norway. We see that some biodiversity impact variables indeed are to a large extent influenced by geography. The cluster distribution between the northern and southern production areas for lice, diseases and overall are much more skewed than those for escapes, bottom surveys and lice treatments. Interestingly, the best cluster is more populated by the norther companies when it comes to lice, but by southern companies when it comes to lice treatments, suggesting that farmers in the north rely more on medicinal treatments. It is possible that medicinal treatments are more commonly used in the north because they tend to be effective only for lower levels of lice due to the development of resistance.

Figure 6 shows a correlation matrix highlighting relations between the singular rankings, the overall ranking, and slaughter weight. The matrix also shows the correlations with share of localities in the north or south, where the latter value has the same magnitude but opposite sign.[11] We find strong correlations between singular rankings and the

[11] The input data to the correlation matrix is presented in Table D.1 in Appendix D.

Table 2
Overall nationwide rating. Input data is all five biodiversity factors annually from 2016 to 2021.

Rank	Company	Total score
1	Cermaq Norway AS	6
1	Gildeskål Forskningsstasjon AS	6
1	Kleiva Fiskefarm AS	6
1	Nova Sea AS	6
1	Wilsgård Fiskeoppdrett AS	6
…	…	…
34	Sulefisk AS	19
35	Blom Fiskeoppdrett AS	19
36	Eide Fjordbruk AS	20

share of localities in the north/south, especially when it comes to lice and diseases. For companies operating in the north, there is a negative correlation with diseases, lice numbers and overall score. For companies with their operations in the south - the opposite is observed. Our results indicate that the overall nationwide ranking is strongly influenced by performance on diseases and lice. We see that operating in the south, as shown in Fig. 5 and Fig. 6, correlates with poor biodiversity impact cluster scores on diseases and lice numbers. This indicates that salmon farmers operating in the northern production areas have an advantage when our model is applied nationwide.

To further examine these correlations, we perform a regression analysis to see how individual scores on the biodiversity variables affect the overall biodiversity score. We run the regression by using the data table shown in Appendix D. The dependent variable is the “Overall clustering score”, while the independent variables are all the singular variable clustering scores in addition to “Slaughter weight 2020″ (in 1000 tonnes) and a dummy variable stating if the company has the most of their localities in south/western part of Norway or the northern part. The results from this regression are presented in Table 3 below.

From Table 3 we can see that being in the best cluster with respect to lice counts or bottom surveys is positively associated with the overall clustering score and that this effect is statistically significant at the 1% level. It can also be seen that diseases are positively associated with the overall clustering score and that this effect is statistically significant at the 5% level. Together, these three biodiversity impact variables are the most important variables explaining the nationwide overall biodiversity

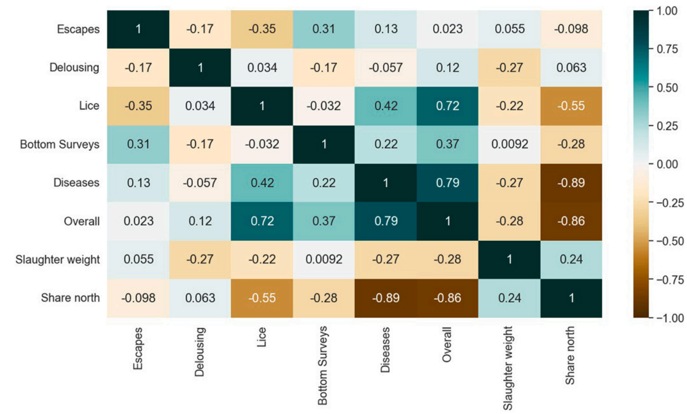

Fig. 6. Correlation between ranking on singular factor rankings, overall ranking, slaughter weight in 2020 and share of localities in north/south.

Table 3
Association between overall biodiversity clustering score and the other biodiversity variables. Standard deviation is shown within the parentheses. Slaughter weight in 1000 tonnes.

	Overall clustering score
Escapes	– 0023
	(0101)
Lice treatments	0121
	(0075)
Lice counts	0410 * **
	(0066)
Bottom Surveys	0423 * **
	(0064)
Diseases	0263 * *
	(0098)
Slaughter weight 2020	0011 *
	(– 0011)
South/west	2245 *
	(1113)
Observations	36
R^2	0928

Note: * $p < 0.1$; * * $p < 0.05$; * ** $p < 0.01$

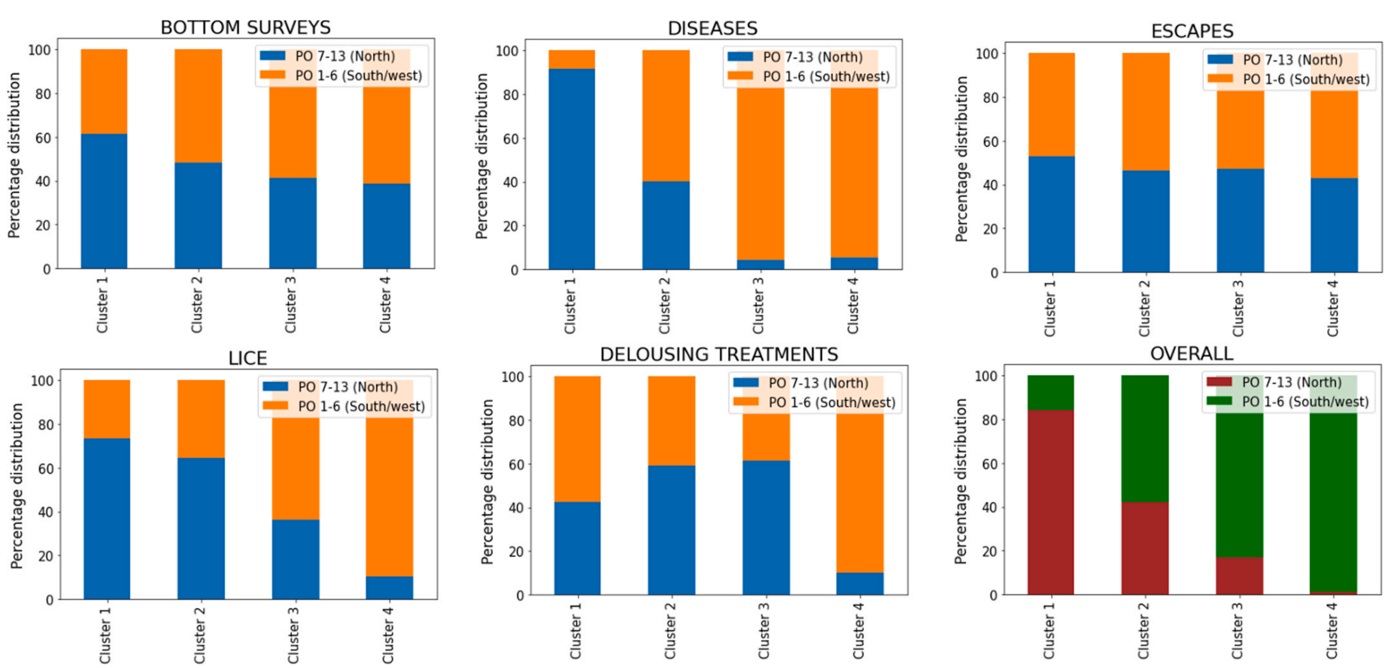

Fig. 5. Cluster distribution with regards to geography.

impact performance comparison. Table 3 also shows that slaughter weight has some effect on the overall clustering score, indicating that bigger companies get slightly worse biodiversity impact scores than smaller companies when compared nationwide. Lastly, we see that companies located mainly in the southern or western regions of Norway have a disadvantage compared to those operating in the northern parts of Norway.

The finding of a geographical (dis)advantage among salmon farming companies in Norway is not surprising, given that localities in the north are dispersed over a bigger area than in the south, hence resulting in a lower locality density. Due to a lower density of localities, salmon farming companies operating in the north are less vulnerable to contamination and transfer of disease and sea lice between localities. At the same time, northern waters are colder, meaning the sea lice propagate slower than in areas with warmer sea water [13]. The north vs. southwest advantage is also reflected in the government's classification of disease zones,[12] in which the 7 northernmost production areas are classified as PD surveillance zones, 5 out of the 6 southernmost production areas are classified as PD fighting zones with more frequent disease outbreaks [25].

Thus, it is clear that companies with localities in the southwestern production areas have a larger and a more serious impact on biodiversity. At the same time, this can be seen as a natural disadvantage outside of companies' control. In order to disentangle this effect from the impact of managerial decisions, we split the data set into two groups: the seven northernmost production areas and the six southernmost areas. This way we are able to compare the companies that operate under similar biological conditions, whose differences are likely to come primarily from measures implemented to combat biodiversity loss. The rankings of the companies operating in the southwestern production areas and in the northern production areas are presented in Tables 4 and 5, respectively.

Comparing Table 4 to the nationwide biodiversity impact rating in Table 2, we see that the same companies end up being the worst performers. However, unlike in the nationwide ranking, the large listed companies Mowi, Salmar, NRS, Lerøy, Måsøval and Grieg Seafood perform well compared to the privately owned salmon farming companies operating in the same region. These six companies end up among the top nine biodiversity impact performers operating in the southwestern areas of Norway out of 20 companies. This result is in line with the FAIRR Initiative Protein Producer Index, as Mowi is the best performing, closely followed by Lerøy Seafood.

A potential explanation for better performance of large companies is that they have better routines due to a more extensive base of experience and resources or a more substantial focus on sustainability to attract investors. Also, the Norwegian government prioritizes sustainability and biodiversity matters when granting production permissions [27], leading to an increase in production for more sustainable companies. Another reason could be that the listed players benefit from synergies in consolidations. In this case, better routines, increased focus on biodiversity and more resources could be utilized when acquiring one of the smaller privately-owned companies.

Table 5 below shows that also in the northern production areas, the listed salmon farming companies perform well. The northern operations of the five listed companies Mowi, Lerøy, Salmar, NRS Farming and Grieg Seafood get placed in the top half of the biodiversity impact performance ranking out of 21 companies. We see that Cermaq Norway is ranked first, similar to the nationwide ranking, followed by Wilsgård Fiskeoppdrett and Nova Sea. However, the other two top-performing companies from the nationwide ranking, Kleiva Fiskefarm and Gildeskål Forskningsstasjon, do not end up among the top performers when compared to their peers operating in the northern production areas. This likely due to their poor performance on lice and disease management relative to the other salmon farming companies operating in the northern production areas.

Next, we run an ordinary least square regression analysis to investigate which singular factors influence the overall scores for the southwestern and northern operating companies separately. The results are presented in Table 6.[13]

When splitting the data set, we see that the sign on the "Slaughter weight 2020″ coefficient becomes negative for both regressions, unlike in the nationwide comparison in Table 3. This indicates that larger companies perform better than smaller companies. This change of sign is mainly due to fact that the scores of the larger, more geographically diversified companies are weakened by their performances in the southwestern productions areas when the companies are compared nationwide. For companies operating in the southwestern region, we see that the biodiversity impact variables lice treatments, lice counts and bottom surveys are major contributors to the overall biodiversity impact performance ranking, all statistically significant at the 1% level. This is different from the regression results nationwide, as the variable lice treatments affect the overall score more in the analysis for the southwestern operating companies than for the nationwide analysis. Similarly, the diseases influence the overall biodiversity impact score for the southwestern operating companies less than in the nationwide regression analysis. This indicates that many companies in the southwestern areas perform similarly on diseases but there exists a large variation among them when it comes to lice treatment method performance. Consistent with the nationwide regression analysis in Table 3, lice counts and bottom surveys still significantly affect the overall score for the southwestern operating companies. From the perspective of managerial insights, this implies that companies operating in the southwestern production areas should focus more on improving their practices related to lice treatments, lice counts and bottom surveys in order to improve their overall biodiversity impact score when compared to their peers in the southwest.

The results from the regression analysis applied to the companies operating in the northern region show that lice treatments do not significantly affect the overall biodiversity impact score, whereas diseases do. Similar to the regression analysis for companies in the southwest and nationwide, the biodiversity variables lice counts and bottom conditions also show statistical significance. These results indicate that companies operating in the northern production areas should focus on lice counts, bottom surveys and prevention of disease outbreaks to improve their overall biodiversity impact score when compared to other salmon farming companies operating in northern Norway.

3.2. Model robustness

To examine the robustness of our model, we perform additional analysis on the data with time series attributes. Our current clustering methodology considers both time series and non-time series data by aggregating them annually. Thus, we examine the robustness of our approach by applying both our methodology and a classical time series clustering to the biodiversity impact variables. We use dynamic time warping to cluster companies based on univariate time series in order to capture the time series aspect of the following biodiversity impact variables: lice treatments, diseases and lice. These three variables can be collected weekly, as opposed to escapes and bottom surveys that have a different data structure unsuitable for time series analysis. Dynamic time warping is a technique to dynamically compare time series data when the time indices between comparison data points do not sync up perfectly [24]. This algorithm is thus suitable to deal with, for example, the data on lice counts. As lice levels are to a certain extent

[12] A disease fighting zone is created around an infected facility, whereas a disease surveillance zone is created outside the fighting zones in order to monitor if the disease has spread from the fighting zone.

[13] The input data for these regression analyses is presented in Tables D.2 and D.3 in Appendix D.

Table 4
Biodiversity impact performance cluster placement in a given year for southwestern production areas (PA 1–6). Note that NRS Farming sold its localities in the southwestern production areas after 2019, leaving them without a score for the last two years in the dataset.

Rank	Company	2016	2017	2018	2019	2020	2021	Total
1	Mowi ASA	1	1	1	1	1	2	7
2	Salmar Farming AS	1	1	1	2	1	2	8
3	NRS Farming AS	2	1	2	1	x	x	9(est.)
4	Lerøy Seafood Group ASA	1	1	2	2	1	2	9
5	Måsøval AS	1	1	1	1	3	2	9
6	Kobbevik og Furuholmen AS	1	1	1	2	1	3	9
7	Tombregruppa	1	1	2	3	2	1	10
8	Hofseth Aqua AS	3	1	1	2	1	2	10
9	Grieg Seafood ASA	1	2	1	1	3	2	10
10	Bremnes Seashore AS	1	2	2	3	1	2	11
11	Alsaker Fjordbruk AS	1	1	1	3	3	2	11
12	Lingalaks AS	2	2	2	3	2	1	12
13	Bolaks AS	3	1	2	2	2	2	12
14	Steinvik Fiskefarm AS	1	2	4	3	2	2	14
15	Firda Sjøfarmer AS	4	1	3	1	3	2	14
16	Eide Fjordbruk AS	4	4	1	3	2	1	15
17	Erko Seafood AS	3	3	3	1	3	2	15
18	Sulefisk AS	1	2	4	1	3	4	15
19	Blom Fiskeoppdrett AS	2	2	3	3	3	4	17
20	Osland Havbruk AS	1	3	1	4	4	4	17

Table 5
Biodiversity impact performance cluster placement in a given year for northern production areas (PA 7–13).

Rank	Company	2016	2017	2018	2019	2020	2021	Total
1	Mowi ASA	3	1	1	1	1	1	8
2	Cermaq Norway AS	2	1	2	1	1	1	8
3	Lerøy Seafood Group ASA	2	1	3	1	1	1	9
4	Wilsgård Fiskeoppdrett AS	1	2	2	1	2	1	9
5	Salmar Farming AS	2	1	3	1	2	1	10
6	Nova Sea AS	3	1	1	1	3	1	10
7	Flakstadvåg Laks AS	1	2	1	2	3	1	10
8	Lovundlaks AS	3	1	1	1	1	3	10
9	Nordlaks Oppdrett AS	3	1	1	2	1	3	11
10	NRS Farming AS	2	1	2	1	2	3	11
10	Grieg Seafood ASA	2	1	2	1	2	3	11
12	Ellingsen Seafood AS	3	1	1	2	4	1	12
13	Kleiva Fiskefarm AS	1	1	1	2	3	4	12
14	Salmonor AS	3	3	1	3	2	1	13
15	SinkabergHansen AS	1	3	3	4	1	2	14
16	Eidsfjord Sjøfarm AS	3	1	3	1	3	3	14
17	Gildeskål Forskningsstasjon AS	1	2	2	2	3	4	14
18	Emilsen Fisk AS	2	3	4	3	2	1	15
19	Bjørøya AS	4	3	1	3	3	1	15
20	Egil Kristoffersen & Sønner AS	3	4	3	1	1	3	15
21	Salaks AS	3	1	3	3	2	4	16

Table 6
Association between overall biodiversity clustering score and the biodiversity impact variables in the southern production areas 1–6 and in the northern production areas 7–13. The standard deviation is shown within the parentheses. Slaughter weight in 1000 tonnes.

	Southern areas	Northern areas
Escapes	0176	0161
	(0105)	(0118)
Lice treatments	0422 * **	0117
	(0065)	(0151)
Lice counts	0284 * **	0258 * *
	(0069)	(0103)
Bottom surveys	0250 * **	0218 *
	(0067)	(0115)
Diseases	0063	0251 *
	(0083)	(0126)
Slaughter weight 2020	− 0019 * *	− 0050 * *
	(0006)	(0022)
Observations	19	21
R^2	0921	0705

Note: * $p < 0.1$; * * $p < 0.05$; * ** $p < 0.01$

temperature-dependent, sea lice levels rise later in the year in the north of Norway than in the south and vice versa [7]. With dynamic time warping, such effects can be mitigated, placing northern and southern operating salmon farming companies in the same clusters although their time series do not align perfectly.

The key question for the dynamic time warping model on time series is whether our cross-sectional clustering approach capture time series variance well enough. If it does, the time series-based model should be able to identify the same companies as top and bottom performers as our K-means clustering approach on cross-sectional data described in Section 2.3. To answer this question, we divide the result tables from our K-means model on singular biodiversity impact variables nationwide into four quartiles. The 1st quartile contains the companies ranked as the top nine best performers. 4th quartile contains the companies ranked as the bottom nine performers. If there is a tie for a ranking spot, cluster placements more recently are weighted more than cluster placements further back in time (e.g., placement in Cluster 1 in 2019 outweighs placement in Cluster 1 in 2017). For the time series clustering, we also use four clusters so that the number of clusters is aligned with the number used in the cross-sectional approach. Four clusters in the univariate time series clustering model is also sufficient to avoid outlier dominance and get at least two clusters containing more than nine companies, making a comparison between our two clustering approaches possible.

Table 7 presents the comparisons between these two approaches, where we illustrate the fraction of equally ranked top and bottom nine performing companies by the cross-sectional and time-series clustering models.

Table 7 shows that the dynamic time warping clustering model is able to capture much of the same trends as our main clustering model. The univariate time series clustering approach aligns well with our main clustering model, correctly placing $\frac{26}{27}$ companies in the 4th quartile of the ranking. It is also highly consistent in the 1st quartile, only missing out on two company placements.

For the lice counts, Tombregruppa is placed in the worst of two big clusters in the time series approach, while it is ranked within the top nine in the cross-sectional model. A misalignment between the two methods also occurs for the lice treatment variable in the dynamic time warping clustering model, where Hofseth Aqua is placed in a medium performing cluster out of three big clusters instead of the cluster with the best performers. The medium-performing cluster also contains Alsaker Fjordbruk, rated among the bottom nine on lice treatments in our main clustering model. Full cluster assignments of the dynamic time warping time series clustering algorithm can be found in Appendix E. We conclude that our model based on the cross-sectional clustering approach in Section 2.3 sufficiently captures time series variance. Therefore, it can be relied on to provide robust results on biodiversity impact performances using time series-structured biodiversity impact variables.

Table 7
The fraction of equally ranked top and bottom nine performing companies in the cross-sectional and the dynamic time warping time series clustering models.

Variable	Correct classifications, 1st quartile	Correct classifications, 4th quartile	Total
Diseases	$\frac{9}{9}$	$\frac{9}{9}$	$\frac{18}{18}$
Sea lice	$\frac{8}{9}$	$\frac{9}{9}$	$\frac{17}{18}$
Lice treatments	$\frac{8}{9}$	$\frac{8}{9}$	$\frac{16}{18}$
Total	$\frac{25}{27}$	$\frac{26}{27}$	$\frac{51}{54}$

4. Conclusion

The investment world has seen an increased interest in ESG factors over the latest decades, and more focus and attention towards biodiversity impacts from financial institutions, authorities and companies. This also applies to Norway's second-largest export industry, aquaculture. In this paper, we develop a company level biodiversity impact assessment, where we rank Norwegian aquaculture companies based on several biodiversity impact variables over time. We utilize publicly available data on lice counts, escapes, diseases, bottom survey scores, and lice treatments. We find that the best performing companies in the ranking are mainly salmon farming companies with localities exclusively in the northern production areas of Norway. Concurrently, the poorest performing companies on the nationwide biodiversity impact ranking primarily consist of companies operating in the southwestern production areas of Norway. Thus, the geographical location has a substantial influence on the overall ranking. Among the biodiversity impact variables that influence the overall rating most are the variables sea lice, diseases and bottom conditions. In the nationwide comparison, we find that performance on escapes and lice treatments does not significantly contribute to the ranking of companies. Third, since our results on a nationwide basis indicate a strong correlation between biodiversity impact performance score and geographic location of the companies localities in Norway, we split the data set into a southern part and a northern part. We rank the companies using our biodiversity impact clustering methodology separately for production areas 1–6 (southwestern Norway) and 7–13 (northern Norway). Our results show that the big listed companies are ranked high on biodiversity impact performance in both parts of the country. In the southern production areas, the five best-performing companies out of 20 are all publicly traded. For the companies operating in the northern areas of Norway, all six listed salmon farming companies are placed among the top half of the 21 northern companies. Overall, the insights provided by our model are particularly helpful for guiding informed and sustainability-oriented investment decisions made by financial institutions and portfolio managers, as they enable a differentiation of companies based on their biodiversity footprint. Redirecting capital towards companies that prioritize biodiversity can also contribute to the adoption of sustainable practices in the aquaculture industry.

We have identified several interesting topics for further research that could complement our findings. First, future studies could employ more relevant biodiversity impact variables such as mortality data, feed-conversion ratios and share of localities that are certified.[14] However, there are certain limitations regarding data quality and accessibility concerning mortality data and feed-conversion ratios. It would also be interesting for further studies to exclude the escape variable and see how the results change, as this is the variable in our analysis with the lowest data quality and biggest uncertainties. Second, additional data sources could be employed by future studies to cover more of the impacts from the salmon farming companies' value chain by investigating biodiversity impacts from activities such as smolt production, feed usage, slaughtering and transport of the salmonids, as well as large scale harvesting of wrasse used as cleaner fish to control lice. Third, further research could include companies on a global scale and thus compare and measure biodiversity impact internationally. Moreover, it would be interesting for further research to see if biodiversity impact analysis could be used to predict future biodiversity impact performance of companies. Lastly, further studies can investigate the relation between biodiversity impact performance and financial performance, analyzing whether companies performing well on biodiversity impact also perform well financially or are valued higher in the financial markets.

CRediT authorship contribution statement

Verena Hagspiel: Conceptualization, Supervision, Writing – review & editing. **Markus Bjørkli Jansen:** Formal analysis, Conceptualization, Methodology, Writing – original draft. **Maria Lavrutich**: Conceptualization, Supervision, Methodology, Writing – review & editing, Writing – original draft preparation. **Gaute Nepstad**: Formal analysis, Conceptualization, Methodology, Writing – original draft preparation.

[14] Environmental certifications such as Global G.A.P, Aquaculture Stewardship Council (ASC) and Best Aquaculture Practices (BAP) are given to fish farming companies if they fulfill a certain number of demands regarding sustainability.

[14] Environmental certifications such as Global G.A.P, Aquaculture Stewardship Council (ASC) and Best Aquaculture Practices (BAP) are given to fish farming companies if they fulfill a certain number of demands regarding sustainability.

Data Availability

Data will be made available on request.

Appendix A. Number of localities per company 2016–2021

Table A.1
Number localities each fish farmer operating alone or as an equal partner as of January 1st the given year. A locality operated only by one company is weighted 1, while a locality operated by partners is weighted at 0,5 each. As numbers for 2016 were inaccessible, we use 2017-numbers as a proxy for the 2016 no. of localities.

Company	2016	2017	2018	2019	2020	2021
Alsaker Fjordbruk AS	27	27	25	23.5	23.5	22.5
Bjørøya AS	6.0	6.0	10.5	10.5	9.0	10.0
Blom Fiskeoppdrett AS	10.5	10.5	10.5	11.5	11.0	13.0
Bolaks AS	11.0	11.0	10.0	11.5	13.5	13.5
Bremnes Seashore AS	26.5	26.5	24.5	22.0	20.0	21.5
Cermaq Norway AS	45.0	45.0	45.0	44.5	44.5	45.5
Egil Kristoffersen & Sønner AS	8	8	8	9	9	8.5
Eide Fjordbruk AS	7.5	7.5	8.0	6.5	5.5	6.0
Eidsfjord Sjøfarm AS	20.0	20.0	19.5	19.0	16.0	17.0
Ellingsen Seafood AS	15	15	13.0	10.0	11.0	11.0
Emilsen Fisk AS	5.0	5.0	4.5	5.0	8.0	9.5
Erko Seafood AS	12.5	12.5	12.5	13	13.0	10.0
Firda Sjøfarmer AS	17	17	17	17	17	16.5
Flakstadvåg Laks AS	6	6	7	7	7	7
Gildeskål Forskningsstasjon AS	4.0	4.0	4.0	4.0	4.0	4.0
Grieg Seafood ASA	32.0	32.0	34.0	35.0	34.0	34.0
Hofseth Aqua AS	6	6	6	6	6	5.5
Kleiva Fiskefarm AS	4.5	4.5	4.5	5.0	5.0	5.0
Kobbevik og Furuholmen Oppdrett AS	5.0	5.0	5.0	5.0	5.0	5.5
Lerøy Seafood Group ASA	101.5	101.5	102.5	100.0	97.0	98.0
Lingalaks AS	10.5	10.5	9.0	9.5	9.5	12.0
Lovundlaks AS	6	6	5	6.5	5.0	6.5
Mowi ASA	152.0	152.0	146.5	139.5	140.0	144.0
Måsøval AS	12.5	12.5	12.0	15.0	16.0	17.5
Nordlaks Oppdrett AS	36.5	36.5	35.5	33.0	34.0	35.0
Nova Sea AS	27.5	27.5	26.5	19.5	19.5	20.0
NRS Farming AS	30.0	30.0	33.5	32.5	26.5	26.5
Osland Havbruk AS	6	6	5.5	4.0	3.5	3.5
Salaks AS	6	6	8	8	8	8
Salmar Farming AS	71.5	71.5	69.0	64.0	64.0	60.0
Salmonor AS	19.5	19.5	19.0	19.0	20.5	20.5
SinkabergHansen AS	12.0	12.0	11.0	8.5	10.0	11.0
Steinvik Fiskefarm AS	7.0	7.0	7.0	7.0	8.0	8.0
Sulefisk AS	5	5	5.5	6	6	7.5
Tombregruppa	9	9	9	7.5	8.0	7.5
Wilsgård Fiskeoppdrett AS	3.0	3.0	3.5	3.5	3.5	3.5

B. Overview of the final set of Norwegian fish farming companies

Table B.1
Overview of the final set of Norwegian fish farming companies analyzed in this paper. Slaughter weight equals metric tonnes slaughtered in 2020. Localities is the number of localities the company operated (or partly operated) at the end of 2021. PA is the number of production areas the company operates in. The last columns state the share of a company's locations in the southwestern production areas (PA 1–6) versus the northern production areas (PA 7–13).

Company	Slaughter weight [tonnes]	Localities	PA	Private/Public	South PA	Northern PA
Mowi ASA	262 000	147	10	Public	65%	35%
Lerøy Seafood Group ASA	170 900	115	6	Public	76%	24%
Salmar ASA	147 700	83	7	Public	58%	42%
Cermaq Norway AS	62 700	48	2	Private	0%	100%
Grieg Seafood ASA	46 900	38	2	Public	42%	58%
Nova Sea AS	42 600	26	1	Private	0%	100%
Nordlaks Oppdrett AS	35 000	37	2	Private	0%	100%
Alsaker Fjordbruk AS	31 000	22	2	Private	100%	0%
NRS Farming AS	30 500	25	3	Public	0%	100%
Sinkaberghansen AS	28 700	29	2	Private	0%	100%
Salmonor AS	28 300	27	1	Private	0%	100%
Bremnes Seashore AS	24 400	26	2	Private	100%	0%
Eidsfjord Sjøfarm AS	17 000	16	3	Private	0%	100%
Måsøval AS	16 300	13	2	Public	100%	0%
Firda Sjøfarmer AS	14 000	17	1	Private	100%	0%
Blom Fiskeoppdrett AS	13 100	12	1	Private	100%	0%
Eide Fjordbruk AS	12 500	10	2	Private	100%	0%

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Table B.1 (*continued*)

Company	Slaughter weight [tonnes]	Localities	PA	Private/Public	South PA	Northern PA
Erko Seafood AS	12 500	11	2	Private	100%	0%
Bolaks AS	11 600	21	1	Private	100%	0%
Bjørøya AS	10 900	21	2	Private	19%	81%
Ellingsen Seafood AS	10 400	10	1	Private	0%	100%
Hofseth Aqua AS	9 500	6	1	Private	100%	0%
Lingalaks AS	9 000	12	2	Private	100%	0%
Lovundlaks AS	9 000	9	1	Private	0%	100%
Flakstadvåg Laks AS	8 400	8	1	Private	0%	100%
Emilsen Fisk AS	8 100	15	1	Private	0%	100%
Tombregruppa	7 600	11	2	Private	100%	0%
Osland Havbruk AS	7 500	7	1	Private	100%	0%
Egil Kristoffersen og Sønner AS	7 000	10	1	Private	0%	100%
Wilsgård Fiskeoppdrett AS	7 000	9	2	Private	0%	100%
Kobbevik og Furuholmen Oppdrett AS	6 800	7	2	Private	100%	0%
Kleiva Fiskefarm AS	6 500	11	1	Private	0%	100%
Gildeskål Forskningsstasjon AS	6 400	8	2	Private	0%	100%
Steinvik Fiskefarm AS	6 300	9	1	Private	100%	0%
Salaks AS	5 000	9	1	Private	0%	100%
Sulefisk AS	3 600	6	1	Private	100%	0%

C. Overall nationwide ranking

Table C.1
Overall rating with yearly cluster placements. Input data is all five biodiversity factors annually from 2016 to 2021.

Rank	Index	2016	2017	2018	2019	2020	2021	Total
1	Cermaq Norway AS	1	1	1	1	1	1	6
1	Gildeskål Forskningsstasjon	1	1	1	1	1	1	6
1	Kleiva Fiskefarm AS	1	1	1	1	1	1	6
1	Nova Sea AS	1	1	1	1	1	1	6
1	Wilsgård Fiskeoppdrett AS	1	1	1	1	1	1	6
6	Bjørøya AS	1	2	1	1	1	1	7
6	Salmonor AS	1	2	1	1	1	1	7
8	Flakstadvåg Laks AS	1	1	1	2	1	1	7
9	Mowi ASA	1	1	1	3	1	1	8
10	Ellingsen Seafood AS	1	1	1	1	2	2	8
11	Lovundlaks AS	1	1	1	1	1	3	8
12	Emilsen Fisk AS	2	2	2	1	1	1	9
13	SinkabergHansen AS	1	2	2	1	2	1	9
14	Salaks AS	1	1	2	2	1	2	9
15	Grieg Seafood ASA	1	2	1	1	1	3	9
16	Eidsfjord Sjøfarm AS	1	1	2	1	1	3	9
17	NRS Farming AS	2	1	2	1	1	3	10
18	Nordlaks Oppdrett AS	2	1	1	2	1	3	10
19	Salmar Farming AS	2	2	2	3	1	1	11
20	Lerøy Seafood Group ASA	2	2	2	4	1	2	13
21	Tombregruppa	3	2	2	1	2	3	13
22	Bolaks AS	3	2	2	3	2	2	14
23	Måsøval AS	1	2	3	3	3	2	14
24	Egil Kristoffersen & Sønner	1	3	2	2	3	3	14
25	Kobbevik Og Furuholmen	1	2	3	3	4	2	15
26	Lingalaks AS	2	2	2	4	2	3	15
27	Steinvik Fiskefarm AS	1	3	4	4	2	2	16
28	Hofseth Aqua AS	3	2	3	3	3	2	16
29	Alsaker Fjordbruk AS	2	2	3	4	3	2	16
30	Osland Havbruk AS	1	3	1	3	4	4	16
31	Erko Seafood AS	3	3	3	3	3	2	17
32	Bremnes Seashore AS	3	3	3	4	3	2	18
33	Firda Sjøfarmer AS	4	3	3	2	3	3	18
34	Sulefisk AS	3	3	4	2	3	4	19
35	Blom Fiskeoppdrett AS	2	3	3	4	3	4	19
36	Eide Fjordbruk AS	4	4	1	4	4	3	20

D. Input clustering score regression analysis

Table D.1
Singular and overall clustering score from K-means clustering of all companies from 2016 to 2021. Including slaughter weight 2020 and south/west variable to indicate whether the company has operations mainly in the south/western part (1) or northern part of Norway (0).

Company	Escape	Delousing	Lice	Bottom surveys	Diseases	Slaughter weight 2020	South/west	Overall
Cermaq Norway AS	7	11	8	11	6	62700	0	6

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Table D.1 (*continued*)

Company	Escape	Delousing	Lice	Bottom surveys	Diseases	Slaughter weight 2020	South/west	Overall
Gildeskål Forskningsstasjon AS	6	18	9	6	7	6400	0	6
Nova Sea AS	8	10	10	9	6	42600	0	6
Wilsgård Fiskeoppdrett AS	11	13	6	9	8	7000	0	6
Bjørøya AS	16	8	10	9	10	11600	0	7
Flakstadvåg Laks AS	6	15	17	6	6	8400	0	7
Salmonor AS	8	7	12	11	9	28300	0	7
Kleiva Fiskefarm AS	6	15	10	9	6	6500	0	8
Lovundlaks AS	8	11	13	9	6	9000	0	8
Mowi ASA	11	12	16	7	11	262000	1	8
Sinkaberghansen AS	15	10	7	15	8	28700	0	8
Emilsen Fisk AS	7	12	10	15	12	8100	0	9
Salaks AS	6	12	14	8	8	5000	0	9
Ellingsen Seafood AS	6	11	15	9	6	10400	0	10
Nordlaks Oppdrett AS	7	12	14	12	6	35000	0	10
NRS Farming AS	6	11	10	13	10	30500	0	10
Eidsfjord Sjøfarm AS	8	12	11	16	6	17000	0	11
Grieg Seafood ASA	8	15	11	16	10	46900	0	11
Salmar Farming AS	10	9	11	11	11	147700	1	11
Kobbevik og Furuholmen Oppdrett AS	6	10	16	6	21	6800	1	13
Tombregruppa	8	6	9	17	14	7600	1	13
Bolaks AS	10	12	13	15	17	13100	1	14
Lerøy Seafood Group ASA	9	7	15	13	16	170900	1	14
Osland Havbruk AS	6	20	18	10	14	7500	1	14
Lingalaks AS	13	8	9	21	18	9000	1	15
Måsøval AS	6	7	17	10	16	16300	1	15
Egil Kristoffersen og Sønner AS	6	14	18	17	6	7000	0	16
Steinvik Fiskefarm AS	6	13	20	14	13	6300	1	16
Alsaker Fjordbruk AS	7	13	19	13	14	31000	1	17
Hofseth Aqua AS	8	9	20	6	20	9500	1	17
Eide Fjordbruk AS	13	17	9	14	19	12500	1	18
Erko Seafood AS	6	13	23	8	20	12500	1	18
Firda Sjøfarmer AS	9	8	23	14	11	14000	1	18
Bremnes Seashore AS	8	11	18	15	19	24400	1	19
Blom Fiskeoppdrett AS	13	11	22	20	17	10900	1	20
Sulefisk AS	6	17	19	16	18	3600	1	20

Table D.2
Singular and overall clustering score from K-means clustering of the companies from 2016 to 2021 for salmon farming companies operating in the northern production areas (PA 7–13) in Norway. Including slaughter weight 2020 in 1000 tonnes.

	Escapes	Lice treatments	Lice counts	Bottom surveys	Diseases	Slaughter weight 2020	Overall
Cermaq Norway AS	8	11	9	10	6	62,7	8
Mowi ASA North	15	9	15	8	10	92,7	8
Wilsgård Fiskeoppdrett AS	11	16	6	10	12	7,0	9
Lerøy Seafood Group ASA North	6	10	8	14	6	41,6	9
Flakstadvåg Laks AS	6	18	19	6	6	8,4	10
Lovundlaks AS	7	12	14	10	7	9,0	10
Nova Sea AS	10	13	12	9	10	42,6	10
Salmar Farming AS North	11	12	11	13	8	62,3	10
Grieg Seafood ASA North	10	11	8	18	12	27,2	11
NRS Farming AS North	6	11	10	14	16	30,5	11
Nordlaks Oppdrett AS	7	13	17	12	8	35,0	11
Kleiva Fiskefarm AS	6	18	12	9	8	6,5	12
Ellingsen Seafood AS	6	12	18	9	8	10,4	12
Salmonor AS	8	6	14	11	17	28,3	13
Gildeskål Forskningsstasjon AS	6	22	12	6	9	6,4	14
Eidsfjord Sjøfarm AS	10	12	13	16	6	17,0	14
Sinkaberghansen AS	15	14	8	15	11	28,7	14
Egil Kristoffersen & Sønner AS	6	15	21	17	9	7,0	15
Emilsen Fisk AS	8	11	12	16	17	8,1	15
Bjørøya AS	20	10	10	10	18	11,6	15
Salaks AS	6	11	18	8	14	5,0	16

Table D.3
Singular and overall clustering score from K-means clustering of the companies from 2016 to 2021 for salmon farming companies operating in the southwestern production areas (PA 1–6) in Norway. Including slaughter weight 2020 in 1000 tonnes.

	Escapes	Lice treatments	Lice counts	Diseases	Bottom surveys	Slaughter weight 2020	Overall
Mowi ASA South	10	11	14	11	8	169,32	7
Salmar Farming ASA South	14	7	11	11	9	85,417	8
Kobbevik og Furuholmen Oppdrett AS	6	11	12	20	6	6,8	9
Lerøy Seafood Group ASA South	9	6	11	16	14	129,29	9
Måsøval AS	6	6	14	12	10	16,3	9
Grieg Seafood ASA South	6	11	15	10	13	19,747	10

(*continued on next page*)

Table D.3 (*continued*)

	Escapes	Lice treatments	Lice counts	Diseases	Bottom surveys	Slaughter weight 2020	Overall
Hofseth Aqua AS	8	9	15	18	6	9,5	10
Tombregruppa	11	6	8	10	17	7,6	10
Alsaker Fjordbruk AS	7	12	15	10	12	31	11
Bremnes Seashore AS	9	9	15	16	16	24,4	11
Bolaks AS	13	10	9	14	15	13,1	12
Lingalaks AS	13	7	7	14	23	9	12
Firda Sjøfarmer AS	9	8	21	10	16	14	14
Steinvik Fiskefarm AS	6	12	17	9	17	6,3	14
Eide Fjordbruk AS	15	18	8	18	14	12,5	15
Erko Seafood AS	6	13	23	17	8	12,5	15
Sulefisk AS	6	16	16	14	16	3,6	15
Blom Fiskeoppdrett AS	14	13	19	14	22	10,9	17
Osland Havbruk AS	6	21	16	11	10	7,5	17

E. Univariate time series clustering

Table E.1
Result of time series clustering on diseases. Hofseth Aqua, Bolaks, Sulefisk and Kobbevik og Furuholmen are outliers with their own clusters. The rest of the companies are split into two clusters, meaning that cluster 1 is to be interpreted as the good cluster and cluster 2 as the bad.

Company	Cluster	Average share of localities with disease per cluster
Bjørøya AS	1	0.0350
Cermaq Norway AS	1	0.0350
Egil Kristoffersen & Sønner	1	0.0350
Eidsfjord Sjøfarm AS	1	0.0350
Ellingsen Seafood AS	1	0.0350
Flakstadvåg Laks AS	1	0.0350
Gildeskål Forskningsstasjon	1	0.0350
Grieg Seafood ASA	1	0.0350
Kleiva Fiskefarm AS	1	0.0350
Lovundlaks AS	1	0.0350
Mowi ASA	1	0.0350
Nordlaks Oppdrett AS	1	0.0350
Nova Sea AS	1	0.0350
NRS Farming AS	1	0.0350
Salaks AS	1	0.0350
Salmar Farming AS	1	0.0350
Salmonor AS	1	0.0350
SinkabergHansen AS	1	0.0350
Wilsgård Fiskeoppdrett AS	1	0.0350
Alsaker Fjordbruk AS	2	0.1936
Blom Fiskeoppdrett AS	2	0.1936
Bremnes Seashore AS	2	0.1936
Eide Fjordbruk AS	2	0.1936
Emilsen Fisk AS	2	0.1936
Erko Seafood AS	2	0.1936
Firda Sjøfarmer AS	2	0.1936
Lerøy Seafood Group ASA	2	0.1936
Lingalaks AS	2	0.1936
Måsøval AS	2	0.1936
Osland Havbruk AS	2	0.1936
Steinvik Fiskefarm AS	2	0.1936
Tombregruppa	2	0.1936
Bolaks AS	3	0.2609
Hofseth Aqua AS	3	0.2609
Kobbevik og Furuholmen	4	0.3481
Sulefisk AS	4	0.3481

Table E.2
Result of time series clustering on lice counts. Egil Kristoffersen & Sønner and Steinvik Fiskefarm are considered outliers. The rest of the companies are split into two clusters, meaning that cluster 1 is to be interpreted as the good cluster and cluster 2 as the bad.

Company	Cluster	Average lice count per cluster
Bjørøya AS	1	0.1282
Bolaks AS	1	0.1282
Bremnes Seashore AS	1	0.1282
Cermaq Norway AS	1	0.1282
Eide Fjordbruk AS	1	0.1282
Emilsen Fisk AS	1	0.1282
Gildeskål Forskningsstasjon AS	1	0.1282

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Table E.2 (*continued*)

Company	Cluster	Average lice count per cluster
Grieg Seafood ASA	1	0.1282
Kleiva Fiskefarm AS	1	0.1282
Lerøy Seafood Group ASA	1	0.1282
Lingalaks AS	1	0.1282
Mowi ASA	1	0.1282
Nova Sea AS	1	0.1282
NRS Farming AS	1	0.1282
Salmar Farming AS	1	0.1282
Salmonor AS	1	0.1282
SinkabergHansen AS	1	0.1282
Wilsgård Fiskeoppdrett AS	1	0.1282
Alsaker Fjordbruk AS	2	0.1959
Blom Fiskeoppdrett AS	2	0.1959
Eidsfjord Sjøfarm AS	2	0.1959
Ellingsen Seafood AS	2	0.1959
Erko Seafood AS	2	0.1959
Firda Sjøfarmer AS	2	0.1959
Flakstadvåg Laks AS	2	0.1959
Hofseth Aqua AS	2	0.1959
Kobbevik og Furuholmen	2	0.1959
Lovundlaks AS	2	0.1959
Måsøval AS	2	0.1959
Nordlaks Oppdrett AS	2	0.1959
Osland Havbruk As	2	0.1959
Salaks AS	2	0.1959
Sulefisk AS	2	0.1959
Tombregruppa	2	0.1959
Steinvik Fiskefarm AS	3	0.2337
Egil Kristoffersen & Sønner	4	0.3242

Table E.3
Result of time series clustering on delousing treatments. Osland Havbruk is the sole outlier in this table. Thus, the rest of the companies are split into three clusters, meaning that cluster 1 is to be interpreted as the good cluster, cluster 2 the mediocre and cluster 3 the bad.

Company	Cluster	Average share of localities with medicinal delousing per cluster
Bjørøya AS	1	0.0190
Bolaks AS	1	0.0190
Cermaq Norway AS	1	0.0190
Eidsfjord Sjøfarm AS	1	0.0190
Firda Sjøfarmer AS	1	0.0190
Grieg Seafood ASA	1	0.0190
Lerøy Seafood Group ASA	1	0.0190
Lingalaks AS	1	0.0190
Mowi ASA	1	0.0190
Måsøval AS	1	0.0190
Nordlaks Oppdrett AS	1	0.0190
Nova Sea AS	1	0.0190
Nrs Farming AS	1	0.0190
Salmar Farming AS	1	0.0190
Salmonor AS	1	0.0190
Tombregruppa	1	0.0190
Alsaker Fjordbruk AS	2	0.0308
Blom Fiskeoppdrett AS	2	0.0308
Bremnes Seashore AS	2	0.0308
Ellingsen Seafood AS	2	0.0308
Hofseth Aqua AS	2	0.0308
SinkabergHansen AS	2	0.0308
Egil Kristoffersen & Sønner	3	0.0444
Eide Fjordbruk AS	3	0.0444
Emilsen Fisk AS	3	0.0444
Erko Seafood AS	3	0.0444
Flakstadvåg Laks AS	3	0.0444
Gildeskål Forskningsstasjon	3	0.0444
Kleiva Fiskefarm AS	3	0.0444
Kobbevik og Furuholmen	3	0.0444
Lovundlaks AS	3	0.0444
Salaks AS	3	0.0444
Steinvik Fiskefarm AS	3	0.0444
Sulefisk AS	3	0.0444
Wilsgård Fiskeoppdrett AS	3	0.0444
Osland Havbruk AS	4	0.1060

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