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Marine aquaculture sites have huge potential as data providers for climate change assessments

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ABSTRACT

In-situ data is essential in understanding climate change in coastal and marine environments, especially in nearshore locations that are challenging for models to simulate and are often lacking in downscaled climate projections. Environmental parameters such as sea temperature and oxygen are often recorded at fish farms, and this information could be useful for observing coastal changes and climate change assessment. For aquaculture, Norway's BarentsWatch portal is one of the most advanced open-data platforms in the sector. The aim of this study was to inspect the weekly sea temperature data collected from salmon lice monitoring within the Fish Health dataset in BarentsWatch and consider if the recorded temperatures could have value for monitoring climate change due to the spatial and temporal coverage of the farm data. Initial inspection of the dataset found many inconsistencies and suspected errors. In total there were 667 sites where suspected errors were removed. Suspected errors amounted to 7797 data points. Following data cleaning there were 1129 sites and 303,792 data points in total, covering much of the Norwegian coastline. The positions offered good insight into the range of conditions, with data from sheltered inner fjords as well as more exposed locations. Analysis of the BarentsWatch temperatures revealed some sites in southern and western Norway that have already experienced temperatures above 20 °C, challenging conditions for Atlantic salmon (*Salmo salar*) aquaculture. The results showed differences between sites within the same production regions due to site-specific characteristics, illustrating the need for more local-scale data that represents the actual conditions the fish experience, rather than a reliance on regional averages. Although the BarentsWatch platform provided some insight into the temperatures experienced at Norwegian salmon farms, the lack of standardised reporting and uncertainties about data collection and aggregated values meant that detailed analysis was not possible at present. The BarentsWatch analysis was complemented by data from two farms that further demonstrated the need for better guidance and standardised data collection and reporting. Standardised data collection and reporting would ensure that data from different farms is directly comparable. When considered in context with other conditions and fish health parameters, more standardised and robust monitoring of water temperatures at farms would aid the identification of potential challenging conditions and allow for more targeted adaptation responses. Improved data collection and reporting in the present day would have huge value in the future by facilitating the creation of long-term datasets spanning multiple decades at hundreds of locations along the Norwegian coastline, offering exceptional insight into coastal climate change.

1. Introduction

The climate is changing in a way that is unprecedented in human history (IPCC, 2021; Hansen et al., 2023; Ripple et al., 2023). Almost all aspects of life will be affected in one way or another (Scheffers et al., 2016). Individuals and organizations need to plan for the future and

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make decisions on how best to adapt to changing conditions (Siders and Pierce, 2021). As aquaculture is important for food security (Garlock et al., 2022), stakeholders across the entire sector need to ensure that adaptation plans and strategies are in place to minimize disruption to food supply. Throughout differing production stages and the wider supply chain, the aquaculture sector will be exposed to a range of challenges from climate stressors such as rising temperatures, storms, extreme weather events, and changes in precipitation (Barange et al., 2018; Falconer et al., 2022; Froehlich et al., 2022; Maulu et al., 2021; Reid et al., 2019; Rosa et al., 2012). Many of the impacts at aquaculture production sites will be site specific (Falconer et al., 2020; Falconer et al., 2022). Thus in-situ data from aquaculture areas is needed to better understand spatiotemporal heterogeneity, identify challenging conditions, develop models for impact assessment, and prioritize appropriate adaptation responses.

Long-term datasets of in-situ observations are essential for monitoring changes in the marine environment (Miloslavich et al., 2018). There are monitoring programs and observation stations all over the world (Jayne et al., 2017; Smith et al., 2018), but the ocean is huge and coastlines are long and complex, meaning observations are still lacking in most areas (Visbeck, 2018). Where observations are missing, averages or values from the nearest available location are often used. However, focusing on averages and ignoring the variability of conditions can underestimate the effects of climate change on organisms as they are influenced by their own surroundings (Thornton et al., 2014; Helmuth et al., 2014). Hence, there is a need for more data to better understand actual conditions, especially when it comes to aquaculture. Most aquaculture species are poikilothermic and are kept in fixed production systems unable to move beyond the farm boundaries. Small changes in environmental parameters, such as temperature, oxygen or salinity or combinations of these, may have huge impacts on the health and welfare of the animal, especially if these changes occur when parameters are already close to levels that are challenging (Dessen et al., 2021; Montes et al., 2018; Oppedal et al., 2011). If the farming environment becomes unfavourable, the animals must be able to tolerate and adapt to the stress, unless production operations and procedures are changed to militate against potential challenges.

Aquaculture sites are found in many coastal areas throughout the world (Clawson et al., 2022), meaning the potential role of aquaculture as a data provider for observing coastal changes and climate change assessment should be considered. Some aquaculture sectors, especially those farming high-value marine finfish such as Atlantic salmon (*Salmo salar*), have entered the era of precision fish farming (PFF) where enhanced data collection and increased digitalization are supporting more data-driven decisions to improve many different aspects of fish production (Føre et al., 2018; O'Donncha and Grant, 2019; Antonucci and Costa, 2020). Salmon aquaculture producers routinely monitor environmental conditions as part of their operational procedures and day-to-day farm management practices. Hence, vast amounts of valuable data is being collected by the salmon sector and this could offer important insights into the marine environment, beyond its use in daily husbandry. Salmon production is widely recognised as one of the most advanced and innovating parts of the aquaculture sector (Asche and Smith, 2018; Kumar and Engle, 2016), and knowledge diffusion improves technology transfer to other species and systems (Kumar et al., 2018). Therefore, lessons learned from data collection and sharing within the salmon industry, can have wider relevance across the entire aquaculture sector.

Norway is responsible for over half of the world's Atlantic salmon production (FAO, 2022), supplying over 1.5 million tonnes in 2022 and is worth more than 100 billion NOK (USD$ 9.6 billion) (Norwegian Directorate of Fisheries, 2023). One of the reasons for Norway's dominance in salmon aquaculture, is its long and complex coastline that provides many locations that are suitable for aquaculture. In 2012, the Norwegian government launched BarentsWatch (www.barentswatch.no), an online web portal that provides information relevant to marine activities in Norway. The Norwegian Coastal Administration (the Norwegian government agency responsible for water transport infrastructure) has lead responsibility and there are 9 Ministries and 32 administrative agencies and research institutes as partners. BarentsWatch collates coastal and marine data from multiple sources and then develops the information into services for end users to access via an interactive web interface. Most of the portal is open to everyone, though there are several restricted sections that are only accessible for authorised agencies (Knol et al., 2018). Much of the data is available for download and use elsewhere, subject to terms and conditions. The Fish Health section provides weekly overviews of certain fish diseases, sea lice levels, and lice treatment for all active salmon farms in Norway. The number of active farms varies slightly each year, but the yearly average number of Atlantic salmon and rainbow trout (*Oncorhynchus mykiss*) sites in seawater for the years 2012–2022 was 990 (Norwegian Directorate of Fisheries, 2023). The farms are found along most of the coastline, across 13 degrees of latitude (58°N – 71°N), from warmer waters in the south to arctic conditions in the north (the Arctic circle is approximately 66.3°N). Data from a large latitudinal range would be useful for climate change assessments as the speed and magnitude of warming varies by location, and the Arctic is one of the areas undergoing faster rates of change (Rantanen et al., 2022).

It is a regulatory requirement that salmon farmers submit a weekly report to the Norwegian Food Safety Authority that includes sea temperature at 3 m depth, salmon lice treatments, and number of salmon lice (Norwegian Directorate of Fisheries, 2012). If temperatures are below 4 °C, then the requirement to count sea lice changes from weekly to biweekly. Although it is a requirement to report sea temperature at 3 m depth, the regulatory guidance does not specify how the sea temperature should be recorded, how the average weekly temperature should be calculated, or what numerical precision (number of decimal places reported) are required for reporting purposes. The lack of detailed requirements for temperature measurements is a likely consequence of the data being collected as part of fish health monitoring, not for environmental monitoring or climate change assessments, and the temperature data is included for context for the sea lice reporting. Ecologists have highlighted the importance of accurate measurements in understanding microclimates and local scale climate influences on species biology (Bramer et al., 2018; Maclean et al., 2021; Staines et al., 2022). Studies have also shown the importance of spatial considerations and understanding individual site conditions in aquaculture climate change studies (Falconer et al., 2020; Falconer et al., 2023), and it is also essential to consider measurement frequency and data aggregation over time, as averages and discrete points may not fully represent the conditions that the aquaculture species are exposed to (Sampaio et al., 2021).

The BarentsWatch platform has now been operating for over 10 years and is considered one of the most advanced aquaculture data platforms at present. Consequently, it is a good case study to explore the prospects and challenges of repurposing aquaculture data for other users and uses, such as climate change. Focusing on sea temperature data reported in the salmon lice dataset in the fish health section of BarentsWatch, the aim of this study was to inspect the data on weekly sea temperature and consider if the recorded temperatures could have value for climate change assessments. The first objective was to examine the quantity and quality of available temperature data within the BarentsWatch salmon lice dataset and investigate the need for data cleaning. The second objective was to examine the spatial and temporal coverage of the farm locations and characterize the temperatures from these locations. The third objective was to look at additional temperature data from two farms in Norway to consider if there is a need for more detailed guidance for data recording and reporting to support use of the BarentsWatch temperatures in climate change assessments.

2. Methods

2.1. BarentsWatch dataset

More than 1000 salmon farms are found along the Norwegian coast, which has been divided by the authorities into 13 aquaculture production regions. Production is not evenly distributed across the regions, as shown in Fig. 1, and not all farms are actively producing fish at the same time. Each week, as part of fish health reporting, the salmon companies upload sea temperatures from 3 m depth for each site that is currently stocked with fish (BarentsWatch, 2022). This data is then made publicly available on BarentsWatch, which updates each day (BarentsWatch, 2022), so it has near real-time data where possible.

The Salmon Lice dataset, which contained weekly sea temperatures at 3 m depth, was downloaded from the BarentsWatch Fish Health section (https://www.barentswatch.no/nedlasting/fishhealth/lice). Selected data were 'all localities with salmonids' from Week 1 in 2012 to Week 30 in 2022 (the earliest to the most recent record at time of download), covering 552 weeks (approximately 10.5 years). The original dataset contained 1453 unique site names, and 1626 unique site numbers. The site numbers that were not associated with a site name were checked in the BarentsWatch web portal and there were 183 sites that were either not found on the register, or not relevant as they were land based or had other reporting exemptions. These 183 sites were removed from subsequent analysis. Further cleaning was required as there were still some mismatches between unique site numbers and site names. For most cases this was due to differences in the spelling of the site name, or a change in name over time, so these were consolidated.

2.1.1. Data cleaning

The dataset was imported to R (version 4.1.2) (R Core Team, 2021) for data exploration and analysis. The data was then filtered by production area, and sea temperatures for each farm were inspected visually using the R packages ggplot (Wickham, 2016) and plotly (Sievert, 2020). There were 281 sites with no recorded sea temperatures, and these were removed. The initial visualization of sea temperatures in each production region showed suspected errors (e.g., values that were too high or low; Fig. 2). Errors occur due to a range of factors when collecting, processing, or uploading data. Data cleaning refers to the steps taken to identify and then repair or remove the erroneous data (Ilyas and Chu, 2019; Wang and Wang, 2020) and in this study it involved manual data inspection and removal of suspected errors. Anomalies within a time series are not always an error and there could have been a temperature event such as a marine heatwave or cold-spell and this was an important consideration when inspecting the data. The data inspection also showed there was no consistency in the numerical precision or number of significant figures reported, some temperatures were whole numbers whilst others included reporting to one or two decimal places. Due to the uncertainties over anomalies and lack of standardised data collection and reporting, it was difficult to establish common rules and thresholds for data cleaning. Hence, identification of suspected errors was subjective rather than rule-based and involved comparing the suspected error to the rest of the time-series at that site as well as comparing it to sea temperatures at other sites within close proximity. The sites were visualised in BarentsWatch and QGIS version 3.16.7 [QGIS Development Team].

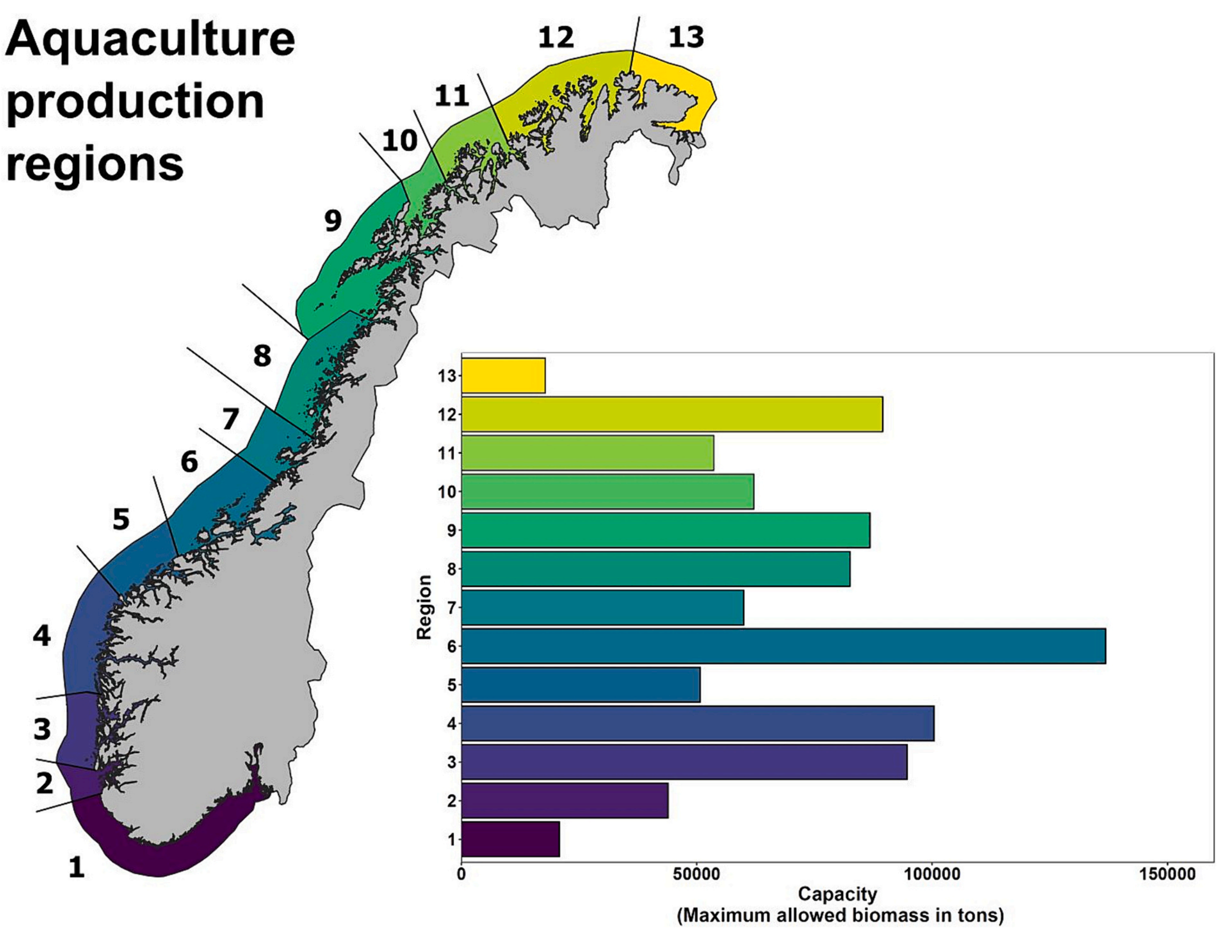

Fig. 1. Norwegian aquaculture production regions (1−13) and the locality licenses' accumulated capacity (maximum allowed biomass in tons) for 2021. Data downloaded from Norwegian Fisheries Directorate.

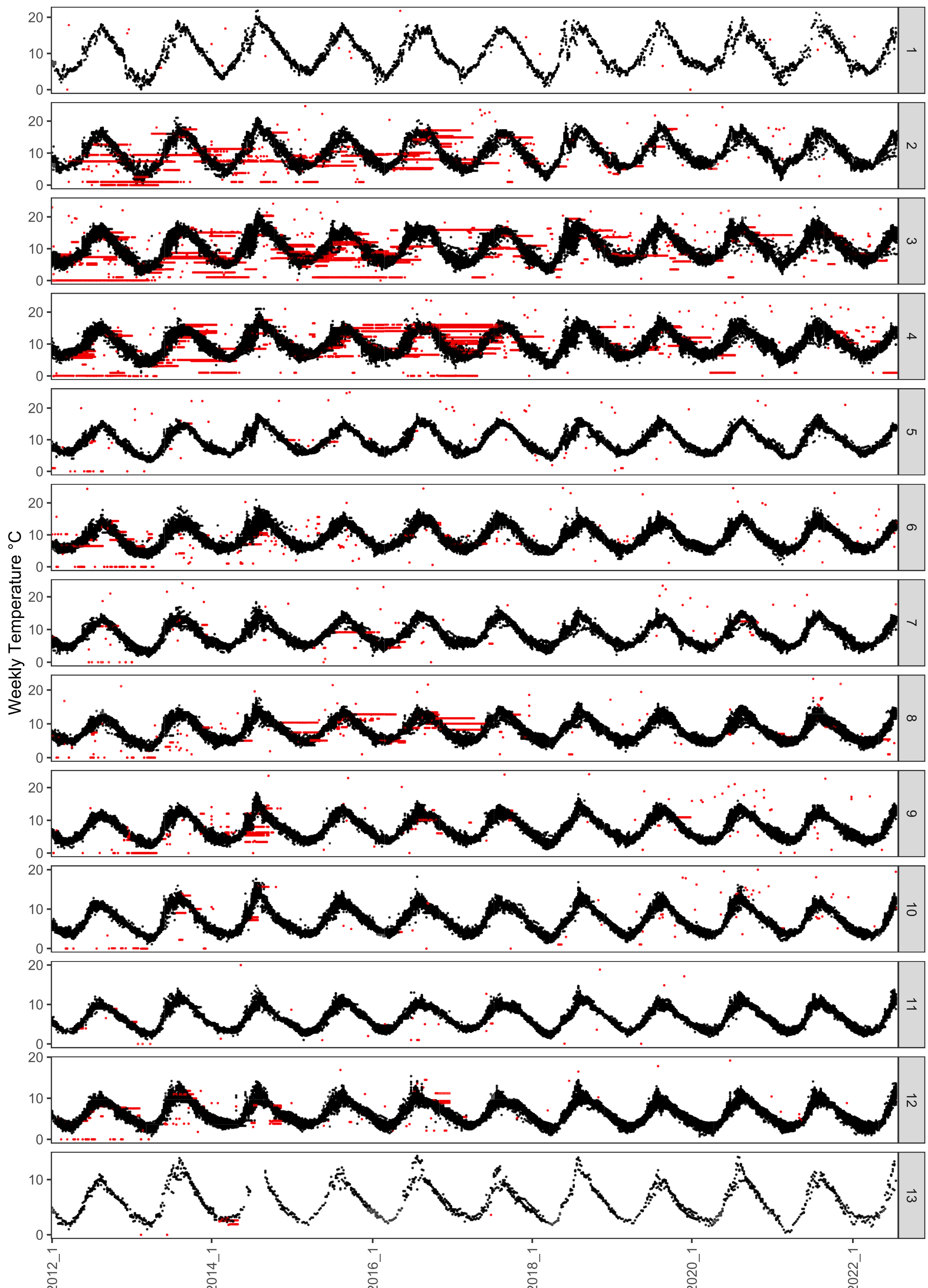

Fig. 2. Sea temperature data for each aquaculture production region (1–13) within the BarentsWatch dataset before cleaning. Within each region, each point represents a temperature recorded at an aquaculture site; Region 1 (12 sites), Region 2 (58 sites), Region 3 (162 sites), Region 4 (153 sites), Region 5 (52 sites), Region 6 (160 sites), Region 7 (84 sites), Region 8 (126 sites), Region 9 (129 sites), Region 10 (80 sites), Region 11 (48 sites), Region 12 (75 sites), Region 13 (9 sites). Plotted data shows the values that were reported in BarentsWatch from Week 1 in 2012 to Week 30 in 2022. Points that were suspected errors are highlighted in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.1.2. *Data analysis*

The temperatures within the cleaned dataset were analysed and visualised using R and QGIS. Data was considered at the individual site level and, where relevant, aggregated to the aquaculture production regions for an overview. Since the data was not complete time-series it was important that any interpretation recognised there were inconsistent and unpredictable gaps. Accordingly, the terms 'lowest reported temperature' and 'highest reported temperature' were used instead of minimum and maximum. For some parts of the analysis, the temperatures were grouped into meteorological seasons: Winter (December – February, weeks 48–53 and weeks 1–8), Spring (March – May, weeks 9–21), Summer (June – August, weeks 22–34), Autumn (September – November, weeks 35–47). Data gaps were calculated using the statsNA command in 'imputeTs' (Moritz and Bartz-Beielstein, 2017).

2.2. Case studies: farm data

Sea temperature data from two Norwegian salmon farms was used to consider if there is a need for more detailed guidance for data recording and reporting to support use of the BarentsWatch sea temperatures in climate change assessments. The temperature data was collected as part of routine farming operations and the farms were anonymised due to commercial confidentiality, henceforth they are referred to as Farm A and Farm B. Both farms were located in northern Norway, Farm A in Region 11 and Farm B in Region 8, and they were selected based on data availability as not all farms record and store temperature measurements at multiple depths or high frequency intervals. Farm A was used to examine temperature differences between depths, and the data was originally collected using sensors from Aanderaa. The monthly average temperature recorded at 09.00 a.m. over the year 2022 was extracted from the Farm A dataset for 3 m and 12 m depth. Farm B was used to examine the effect of temporal averages and summarizing data, and the data was originally collected using sensors from Akva Group. Temperature measurements recorded at 15-min intervals were extracted from the Farm B dataset for January 2019.

3. Results

3.1. BarentsWatch data cleaning

Prior to data cleaning there were 1147 sites that had at least one recorded temperature value (Table 1). Production Regions 3, 4 and 6 had the most sites and the total observations, whereas Region 1 and Region 13 had the least sites and total observations. There were 7797 data points removed during cleaning, from 667 sites. There were 475 sites where <10 data points were removed (of which 310 sites only had 1 or 2 data points removed). There were 15 sites that had over 100 data points removed, and the highest number of removals at any site was 175. After cleaning there were 1129 sites with at least one reported temperature.

The overall distribution of the number of observations per site before and after cleaning are shown in Fig. 3. The maximum number of potential observations at a site was 552 (Week 1 2012 to Week 30 2022), but there were no sites that had data for every week. There were two sites in Region 8 that had over 500 observations (before and after cleaning), but all other sites in the dataset had less than 500 observations. The distributions of number of observations per site varied between production regions. Regions 1 and 13 both had the lowest number of sites overall (12 and 9 sites respectively), but most Region 1 sites had a higher number of observations than the sites in Region 13. Notably, Region 13 had the lowest median number of observations of all regions, before and after cleaning. Lice counts only take place biweekly when temperatures are less than 4 °C, which may affect the number of recorded observations in this region.

The salmon farm sites in the dataset covered a wide range of physical environments (Fig. 4), including fjords (Fig. 4A), coastal and more exposed (Fig. 4B), and island archipelagos (Fig. 4C). Some areas have more data than others. For example, there were sites with a relatively high number of observations (>300) throughout most of Hardangerfjorden (Fig. 4A), one of the longest fjords in Norway and an area with a long history of salmon farming. In contrast, many of the sites in Lofoten and Vesterålen (Fig. 4C) had lower number of observations (⟨300).

3.2. BarentsWatch data gaps

Table 2 provides an overview of some of the data gaps within the cleaned dataset when all the data was organised from Week 1 in 2012 to Week 30 in 2022. Gaps were weeks where there were missing values rather than a value and could refer to either one single missing value or consecutive missing value. The missing value was either there in the original dataset (indicating data not recorded or reported) or introduced through the cleaning process as the value was a suspected error. The analysis revealed that every site in the dataset had at least one gap, the highest number of missing values at any site was 546 (98.9 % of the time-series) at farms in Region 9 and Region 11, and the lowest number of missing values at any site was 31 (5.6 % of the time-series) at a farm in Region 8.

3.3. BarentsWatch temperature analysis

The highest reported temperatures were found in the south and west (Fig. 5A). There were 70 sites that reported a highest temperature ≥ 20 °C, almost all of these sites ($n = 69$) were located in Regions 1–4, and the remaining site was in Region 6. The highest reported temperature was 23.06 °C at a site in Region 3. For colder temperatures, the spatial pattern is slightly different, as the lowest reported temperatures were found in the north, and in the south and west (Fig. 5B). There were 26 sites that had a lowest reported temperature ≤ 1 °C, of which, 9 sites were in Region 1, 8 sites were in Region 2, 4 sites were in Region 12, 3 sites were in Region 13 and there was 1 site each in Region 6 and Region 11. The lowest reported temperature was 0.1 °C at two sites in Region 1. The reported temperatures revealed large temperature ranges for many sites, particularly in the South. There were 19 sites that had a highest reported temperature > 20 °C and a lowest reported temperature < 2 °C, these sites were located in Regions 1, 2 and 3.

The temperature differences along the coastline were evident when the data was aggregated to regional level (Fig. 6). As expected, the regions furthest north (11−13) had colder weekly temperatures than those further south. Over the ten-year period, Regions 1–10 contained sites

Table 1
Overview of the temperature observations within the BarentsWatch dataset before and after cleaning. Lice counts only take place biweekly when temperatures are less than 4 °C, which may affect the number of recorded observations.

Production region	Number of sites with at least one observation			Total number of observations		
	Before	After	Difference	Before	After	Difference
Region1	12	12	0	4215	4189	−26
Region2	58	57	−1	18,647	17,219	−1428
Region3	162	160	−2	51,155	48,990	−2165
Region4	153	152	−1	46,898	44,768	−2130
Region5	52	49	−3	14,870	14,766	−104
Region6	160	158	−2	45,620	45,253	−367
Region7	84	82	−2	17,373	17,201	−172
Region8	126	122	−4	30,789	30,207	−582
Region9	129	127	−2	27,560	27,234	−326
Region10	80	79	−1	19,931	19,786	−145
Region11	48	48	0	11,940	11,893	−47
Region12	75	75	0	20,989	20,713	−276
Region13	9	9	0	1602	1573	−29
Total	**1147**	**1129**	**−18**	**311,589**	**303,792**	**−7797**

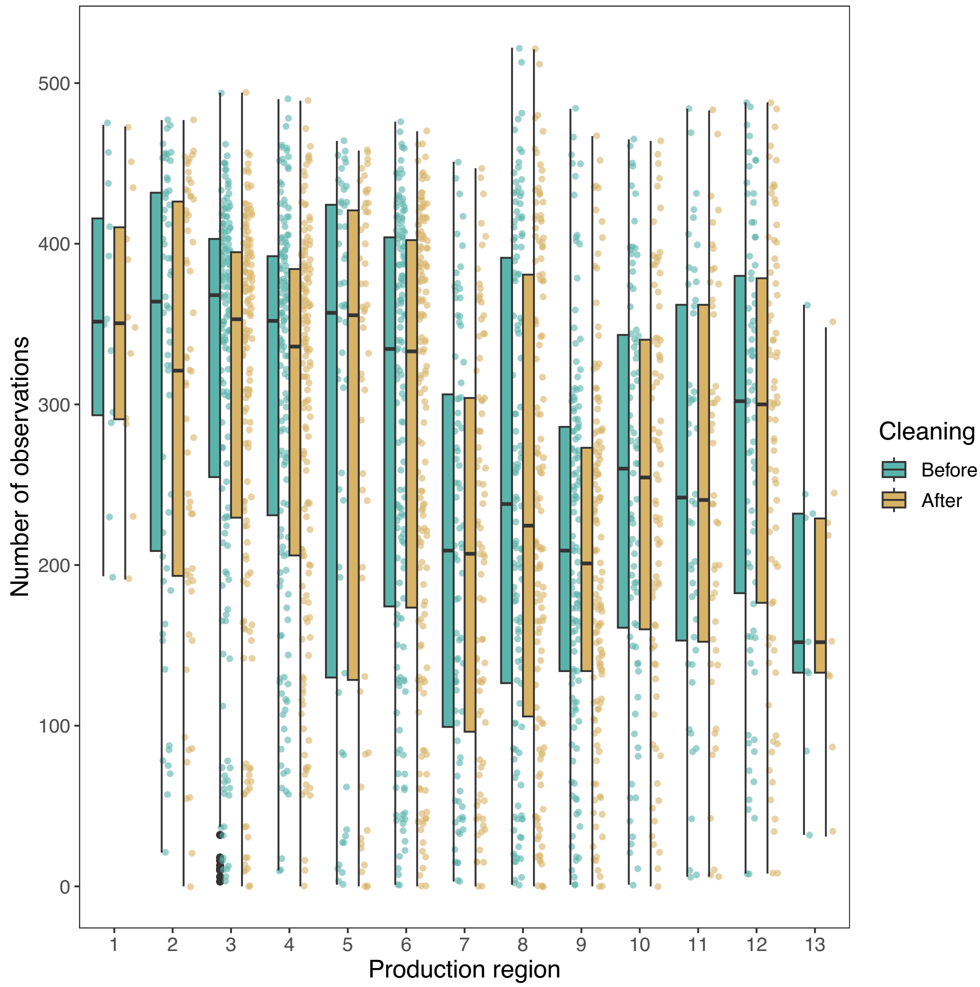

Fig. 3. Hybrid boxplot (half boxplot and half scatterplot) created with ggpol (Tiedemann, 2020) showing the distribution of observations before and after cleaning for each farm in the 13 aquaculture production regions.

that reported weekly temperatures that exceeded 16 °C, whilst Regions 1, 2, 3, 4 and 6 reported weekly temperatures above 20 °C. These temperatures are sub-optimal for salmon production and challenging for salmon health (Handeland et al., 2000; Hevrøy et al., 2013; Falconer et al., 2020). Temperature spikes were evident in some weeks which suggests there was an unusual temperature event at some point in the 10.5 years (e.g., a marine heatwave at one or more sites). However, without further investigation using more detailed datasets from farm companies, this should only be considered as an indication that there may have been an unusual event, as there may have been erroneous data-points missed during cleaning.

Intra-annual and inter-annual variability in recorded temperatures was seen in each of the regions (Fig. 7). Similar patterns of distribution can be seen across different regions in some of the years, for example the spring of 2018 for Regions 1–3, which may be indicative of similar conditions at that time due to weather or climatic factors. However, it is difficult to comprehensively analyse trends and anomalies due to the data gaps (Section 3.2) which influence the distributions. Nevertheless, the results illustrate the potential insight that this dataset could provide if there were fewer gaps.

3.4. Case studies

3.4.1. Depth

Temperature measurements from Farm A were used to explore data that can be obtained by farmers, and evaluate differences between depths in order to demonstrate the need for consistency when taking measurements. They also highlight why single depth measurements may not capture the range of conditions the fish are exposed to (see e.g., Noble et al. (2018)). The monthly average temperatures recorded at 09.00 a.m. at 3 m and 12 m depth at Farm A are shown in Fig. 8. At 3 m depth, the minimum temperature was 2 °C (in March) and maximum was 12.5 °C (in July), whilst at 12 m depth there was a narrower temperature range, with a minimum of 2.1 °C (in March) and maximum of 10.3 °C (in August). At the start of the year temperatures were similar at both depths, but in summer months the temperatures at 3 m depth were 2 to 4 degrees higher than temperatures at 12 m depth. Towards the end of the year, the temperatures at 3 m decreased faster than those at 12 m depth, and in contrast to the summer months, the water at 3 m depth was colder than the water at 12 m depth. Monthly average temperatures were in used in Fig. 8 for visualization purposes to show the difference between depths, but it is important to recognize that there is variability in monthly average temperatures that may mask the actual conditions experienced by the fish (see Section 3.4.2).

3.4.2. Time

Temperature measurements from Farm B were used to explore data that can be obtained by companies and evaluate differences between single discrete point measurements and averages over time. In January 2019 the Farm B measurements at 3 m depth ranged from 4.3 °C to 7.8 °C, with a mean temperature for the month of 6.5 °C (Fig. 9A). The mean temperatures for the month, each week and each day were calculated based on all the measured values which were approximately 15-min apart. The mean temperature for the month is a coarse

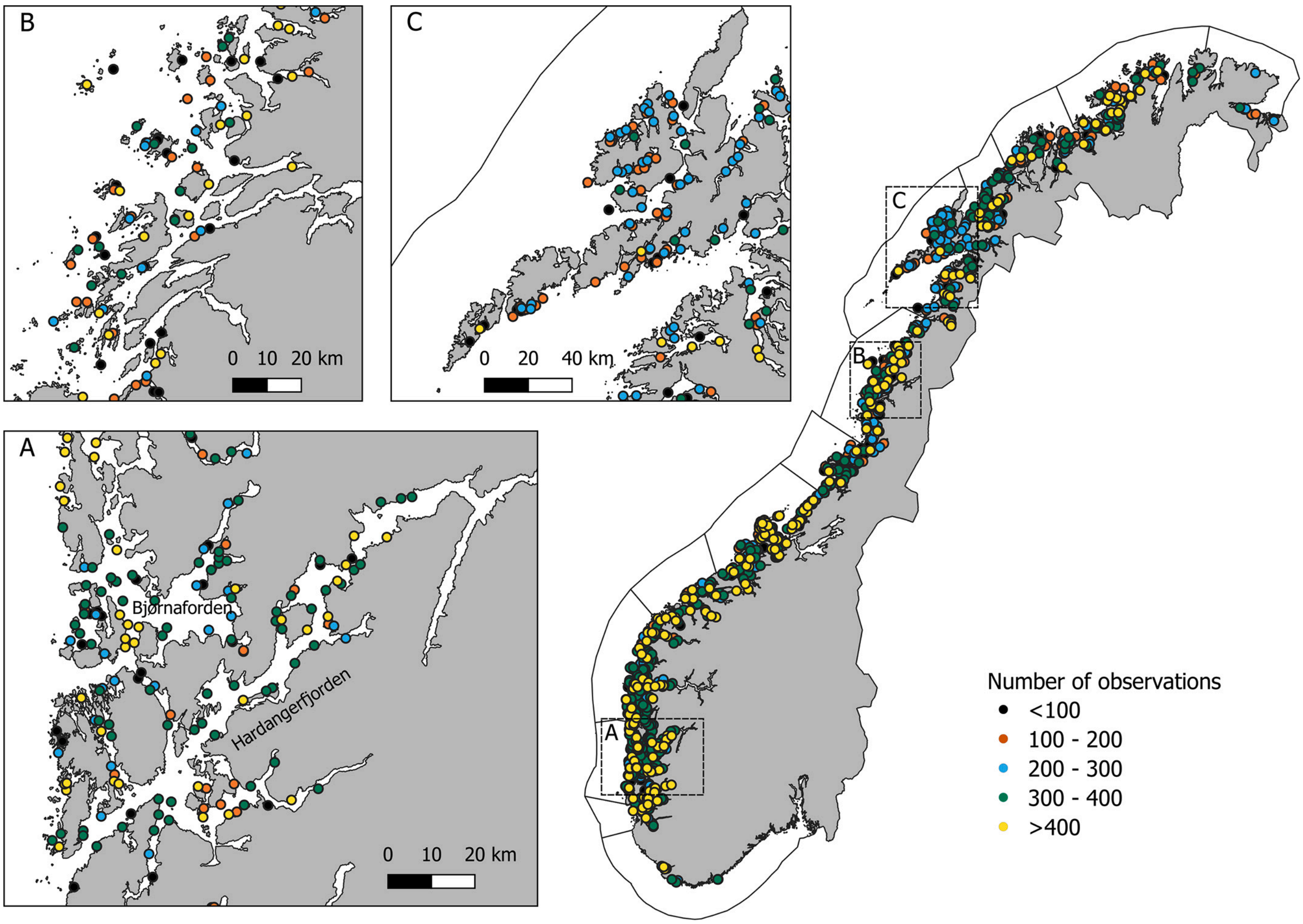

Fig. 4. Total number of weekly temperature observations per site (after cleaning). To show detail, three areas are highlighted in individual zoom boxes: A) Hardangerfjorden and Bjørnaforden in the South, B) Helgelandskysten, C) Lofoten and Vesterålen islands.

Table 2
Overview of the longest gaps and number of gaps (of any size) across the cleaned dataset. A gap refers to a week where temperature is not available (missing value), either because it was absent in the original dataset or because the data point was removed as part of this study.

Aquaculture production region	Highest number of missing values at any site	Lowest number of missing values at any site	Median number of missing values across all sites	Maximum gap between observations at any site	Minimum longest gap between observations at any site	Median longest gap between observations across all sites	Highest number of gaps at any site	Median number of gaps across all sites	Lowest number of gaps at any site
Region 1	361	79	201.5	273	21	74.5	19	12	4
Region 2	531	75	231	520	18	70	47	13	2
Region 3	543	58	196.5	543	21	57	30	10	1
Region 4	542	63	215	541	19	68	25	10	1
Region 5	543	94	193	542	18	69	28	9	2
Region 6	545	82	218.5	545	21	89.5	26	8	1
Region 7	537	49	340	536	22	162	23	6.5	2
Region 8	538	31	311	537	13	178	33	7	2
Region 9	526	21	267	502	13	116	32	8	2
Region 10	541	88	296	525	23	124	16	7	1
Region 11	546	69	311.5	542	18	143	25	7	1
Region 12	544	64	252	543	17	126	17	7	2
Region 13	521	204	400	494	73	229	12	7	3

representation of the range of measured temperatures and does not capture the change in temperature over the month, whereas the averages for the weeks indicate there is a decrease in temperature over the month. The mean temperature for Week 1 (31st December – 6th January) was 7.0 °C, Week 2 (7th – 13th January) was 6.3 °C, Week 3 (14st – 20th January) was 6.3 °C, Week 4 (21st – 27th January) was 6.4 °C, and Week 5 (28th January – 3rd February) was 6.1 °C. The weeks follow the ISO week system so Week 1 started on 31st December 2018, and Week 5 included 4 days at the end of January 2019 and 3 days in February 2019.

Although the mean for the week is a better representation of the temperatures than the average for the month, Fig. 9B shows that mean temperatures for the week do not necessarily represent conditions on individual days as the temperature can vary throughout a day. In Week 3

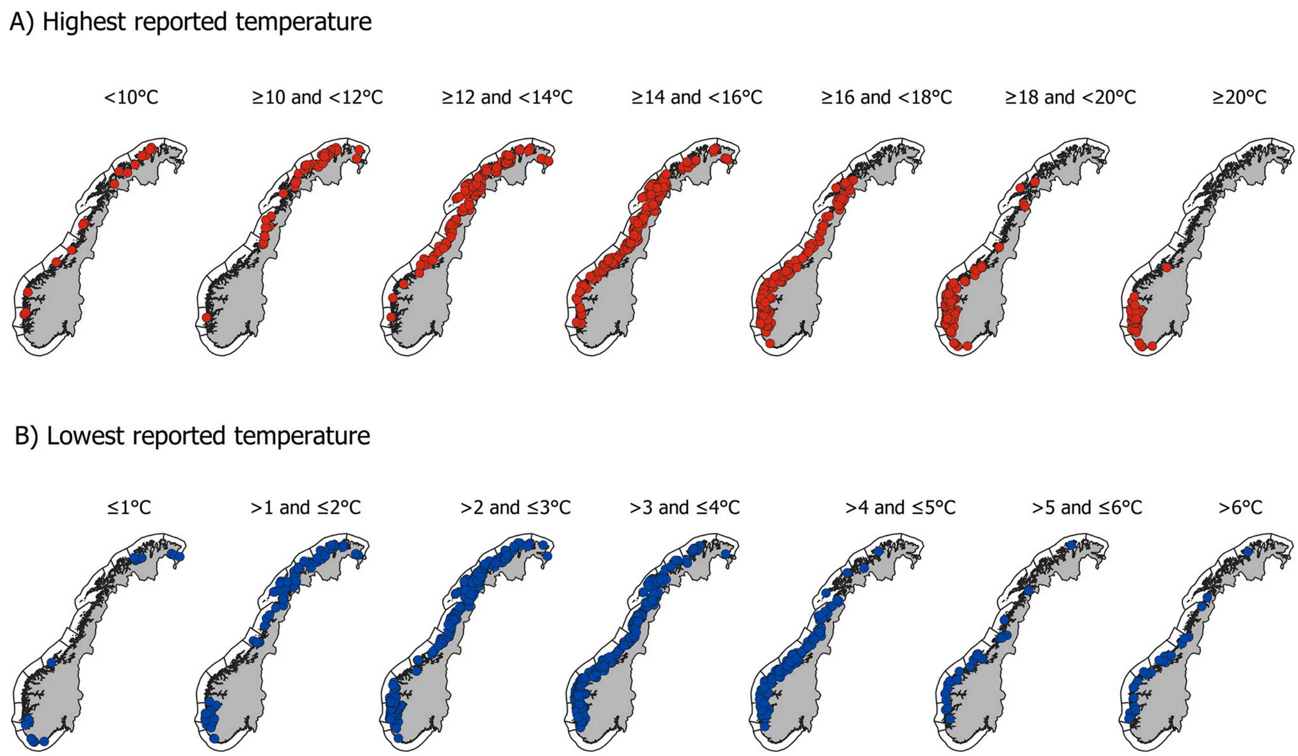

Fig. 5. Sea temperature data extracted from BarentsWatch for each salmon farm (Week 1 2012 – Week 30 2022). A) Highest reported temperature at each site and B) lowest reported temperature at each site. Note: The data is discontinuous and should not be interpreted as maximum and minimum temperature for each site.

the mean temperature was 6.7 °C for 14th January, 6.6 °C for 15th January, 6.9 °C for 16th January, 6.9 °C for 17th January, 5.2 °C for 18th January, 5.5 °C for 19th January, and 6.4 °C for 20th January. The temperatures across Week 3 show that it is difficult to generalise the temperature at this site as some days may have relatively stable temperatures (e.g. 15th January), others may have more fluctuating temperatures (e.g. 20th January) and then there may be other days when the temperatures increase or decrease from start to finish (e.g. 18th and 19th January). The data from the 18th of January (Fig. 9C) also highlights why extracting single discrete measurements from a day is also not an accurate reflection of the range of conditions. At 07.30 am on the 18th of January, the temperature was 5.1 °C, and four hours later, at 12.30 pm the temperature was 5.4 °C, and a further four hours later, at 17.30 pm the temperature was 5.7 °C. The discrete measurements only give a snapshot of part of the day and so the temperatures miss the minimum of 4.3 °C and maximum of 7.1 °C. Furthermore, if these three selected timepoints were used together as a sample of the temperatures throughout the day, then they would suggest that temperature increased, which is contrary to the decline in temperature that was actually recorded over the 24-h period with the 15-min measured intervals.

4. Discussion

This study considered if aquaculture industry data originally collected for sea lice monitoring purposes and shared on the Norwegian BarentsWatch platform could be valuable for climate change assessments. Temperature data from 3 m depth was available for over 1000 farm sites, covering most of the Norwegian coastline, and 13 degrees latitude (58°N to 71°N). The latitudinal range of sites is useful for climate change assessments as some areas, such as the Arctic, are warming faster than others (Rantanen et al., 2022). Furthermore, the sites in BarentsWatch covered a wide range of farming conditions from sheltered, inner fjord, to more exposed, open coast. The results show that the reported temperatures between the individual sites varied considerably, indicating that regional or national averages can under- or over-estimate site-specific temperatures. The variability of farm conditions confirms the need for local-scale monitoring to support climate change assessments for aquaculture (Falconer et al., 2020; Stavrakidis-Zachou et al., 2021). However, our analysis of the BarentsWatch dataset has revealed some challenges that need addressed if the dataset was to be used for climate change monitoring.

In Norway, there are other sea temperature data sources available and like BarentsWatch, they all have their strengths and limitations. The Institute for Marine Research (IMR) maintains 8 hydrographic stations spread across the Norwegian coast, and these have long-term monthly temperature records, but they are found at more exposed locations (Smith-Jonsen and Sagen, 2022) compared to most aquaculture sites (Falconer et al., 2023). The Norwegian Environment Agency runs the ØKOKYST monitoring program which monitors conditions in some fjord and coastal areas, typically through monthly sampling since 2013 and reports are published one year after data collection (Norwegian Environment Agency, 2023). In comparison to the IMR hydrographic stations and the ØKOKYST programme, the BarentsWatch data is weekly and reported in near-real time, and the aquaculture companies also have their own higher frequency datasets, as shown with the example in Section 3.4.2. However, there are hundreds of aquaculture companies involved in collecting and reporting the data to BarentsWatch which increases risks of incompatible data due to the different approaches used for data collection, aggregation, and documentation. In addition to the fixed stations, the Norwegian Research Institute for Water Research (NIVA) have the FerryBox Ships of Opportunity, where sensors are installed on ferries (between Kirkenes in the north and Bergen in the south, and Tromsø and Longyearbyen in the north) and record temperature and other water quality measurements at a depth of 4 to 7 m once every minute along the fixed routes, providing a transect monitoring approach over an area (NIVA, 2023). The FerryBox is an example of using existing activities (transportation) to collect in-situ data, suggesting that other marine activities could also contribute useful information. Furthermore, sea surface skin temperature estimates from satellite remote sensors using, e.g., infrared radiometry, are openly

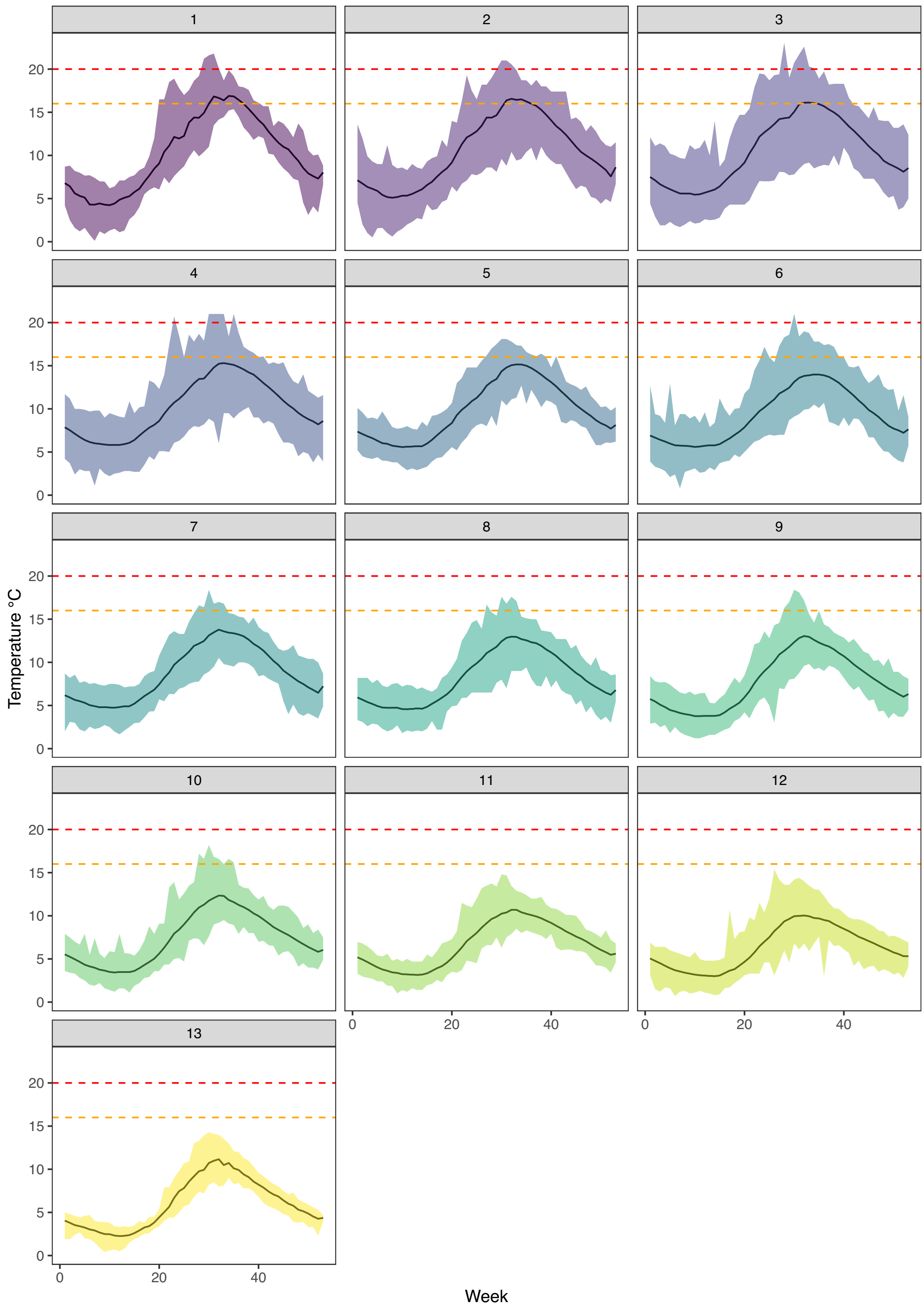

Fig. 6. The highest and lowest reported values in each Norwegian aquaculture production region (1–13) for each week of the year. Data from BarentsWatch (Week 1 2012 to Week 30 2022). The black line represents the mean of the dataset, not necessarily the mean temperature in that region. The orange and red dashed lines show 16 °C and 20 °C respectively, as indications of temperatures that are sub-optimal and challenging for salmon (Handeland et al., 2000; Hevrøy et al., 2013; Falconer et al., 2020). Week 53 only occurs in certain years (2015, 2020) due to the ISO week date system. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

available from oceanographic and meteorological organizations (e.g., EUMETSAT). Data on sea surface skin temperatures, covering the seawater surface layer down to about 0.2 μm depth, i.e., the atmosphere-ocean interface, play a key role in climatology (WMO, 2016). These data can be used in models to estimate temperatures beneath the skin layer. Satellite temperature readings are, however, limited in their spatial resolution, which makes them less suited for monitoring complex coastal environments and fjords, and infrared temperature readings are also limited to areas without cloud cover (Emery et al., 2001; Kara and Barron, 2007; Merchant et al., 2019). In addition to these other

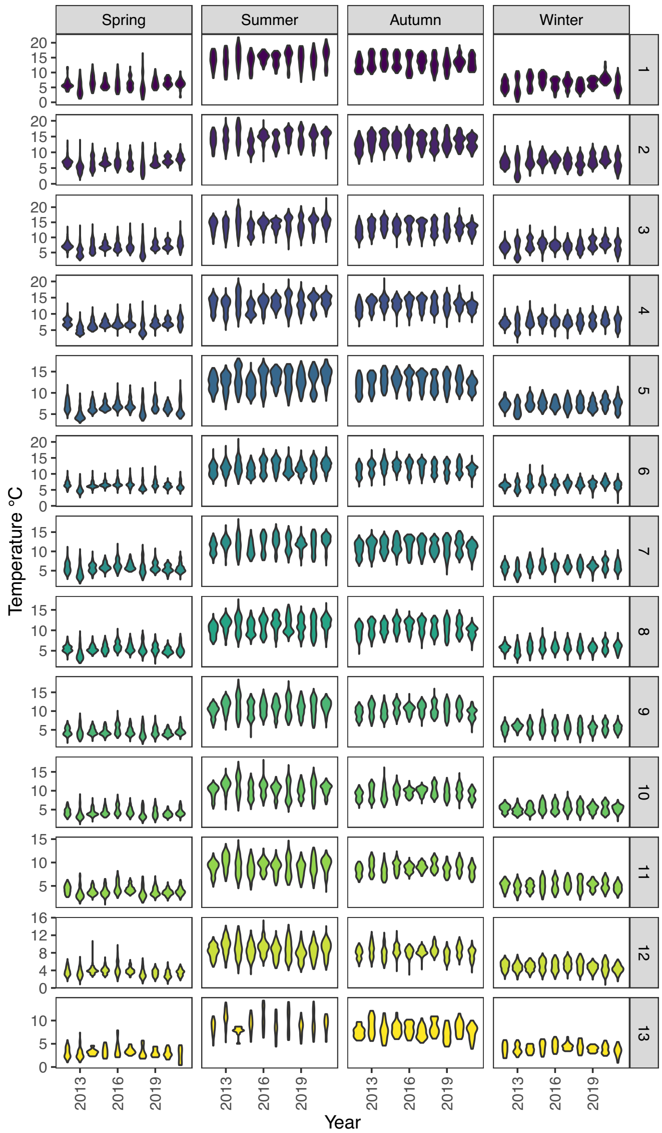

Fig. 7. Violin plots showing the seasonal distribution of reported temperatures for each year (2012–2021) from each region. The number of sites were different across the production regions and data gaps also have an influence on these distributions, which limits some of the interpretation of these results.

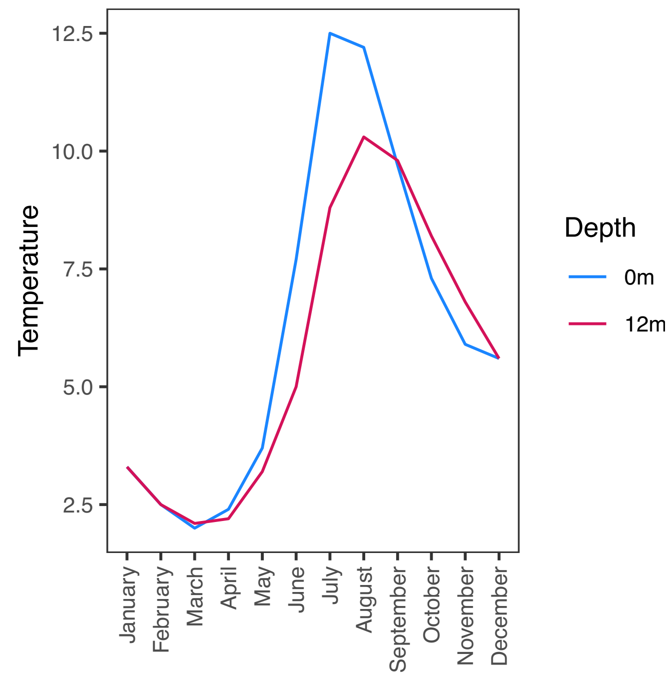

Fig. 8. The average monthly temperature for 09.00 a.m. at 3 m and 12 m depth over 2022 at Farm A.

temperature data sources and complementing the data that is already available, the aquaculture sites offer a unique insight into Norwegian coastal conditions, as farms are at fixed positions throughout the coast and some farms have stayed in the same location for many years and decades. The spatial and temporal scale, as well as the frequency of data provided by the aquaculture companies for all the sites in BarentsWatch would be very difficult to replicate in research projects and prohibitively expensive for government funded monitoring programs. Thus, the local-scale data collected for aquaculture purposes could also potentially support studies on other activities, the coastal ecosystem, and biodiversity (Mieszkowska et al., 2014; Gissi et al., 2021). In terms of spatial and temporal coverage, the aquaculture sites are valuable for climate change assessments.

The original downloaded dataset required a considerable amount of cleaning before use, which was time consuming and challenging. Real-world environmental data is often messy (Gibert et al., 2018), so it is not a surprise that the dataset required cleaning, but this does present some challenges for use in climate change assessments, and other purposes. Data users are likely to employ different data cleaning processes, so consistency in data use would be improved considerably if cleaning occurred before data is reported or made openly available. Manual data cleaning done by end users is time-consuming and is also subjective (Ilyas and Chu, 2019), so data cleaning by one person may not produce the same cleaned dataset as another. Even though steps were taken in this study to assess the likelihood of errors, there is still the risk that an extreme value was not an error and was removed, thereby missing an important event and/or variability across an area. There are automated data cleaning approaches, including techniques using machine learning and artificial intelligence, however these still require people to provide domain knowledge to decide what values need repaired, how they should be corrected and at what stage any changes should be made (Chu et al., 2016; Ilyas and Chu, 2019). Reduction of errors in earlier stages, through improved data collection, recording, auditing, and processing, is important for improving the applicability and utility of the data, especially when it has potential utility for a range of diverse stakeholders and end users. Data quality control schemes, setting clear criteria for the evaluation of the data based on domain knowledge and expert consensus, can be implemented upstream from the end user to ensure a greater quality and accuracy of the delivered data product (see e.g., Bushnell (2015) and Cummings (2011)). Data-driven decision support systems are becoming more important throughout the aquaculture sector (Føre et al., 2018; Yang et al., 2021) so data quality is of utmost importance as erroneous or incomplete datasets may be misleading and lead to poor conclusions or wrong assumptions in models, machine learning and artificial intelligence applications.

A major challenge when implementing and operationalizing a national-scale data platform with many different data sources, is achieving consistent and comparable data. The near-surface layer of the sea is subject to considerable temperature variation in space and time, due to the complex effects of atmospheric conditions, such as wind, rain, and cold fronts, as well as diurnal variations in, e.g., heat flux (Soloviev and Lukas, 2013; Ward, 2006). In fjords, freshwater runoff may also influence spatio-temporal temperature variation through its effects on fjord circulation and vertical mixing (e.g., Haakstad et al. (1994)). The data for Farm A, for example, shows how sea temperatures vary with depth, and this has important implications for farmed fish (Johansson et al., 2009; Johansson et al., 2006; Oppedal et al., 2011). Without clear

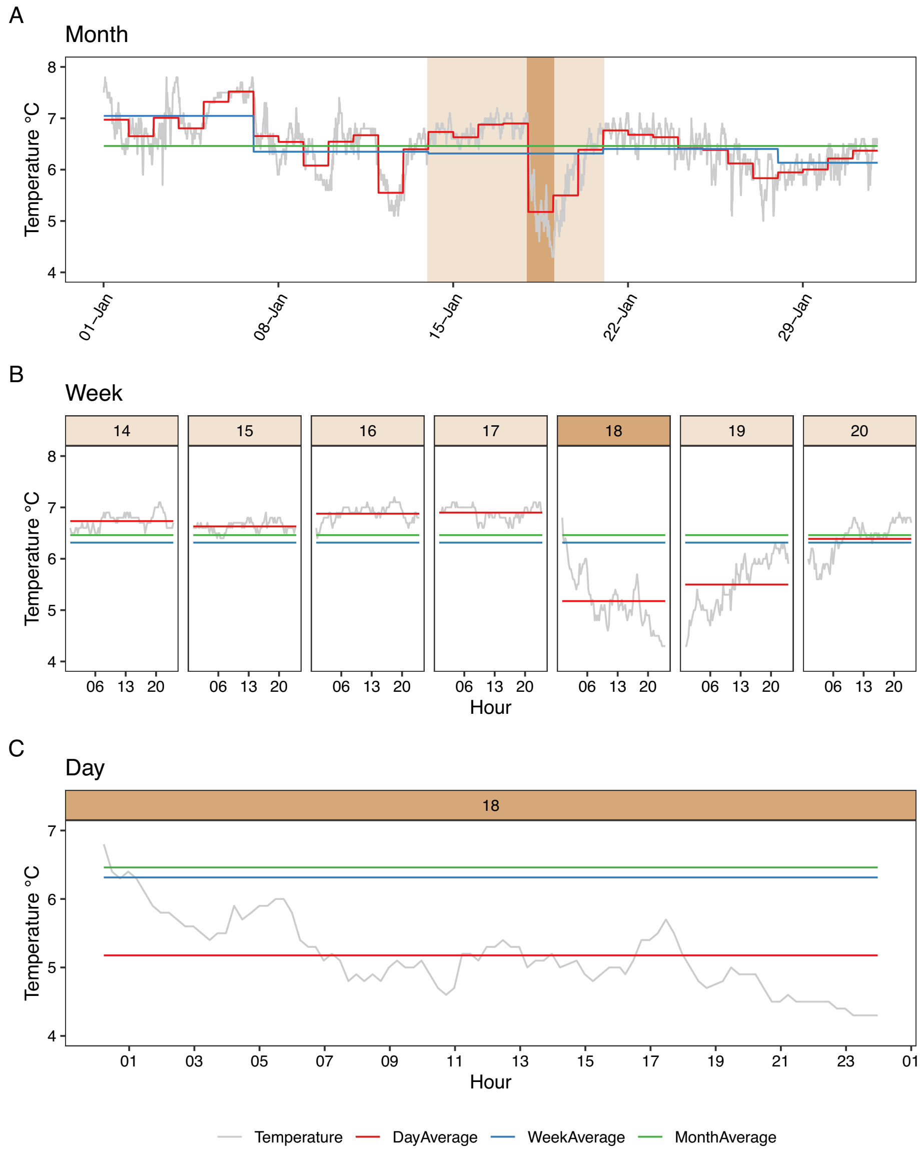

Fig. 9. Temperature recorded at Farm B at 3 m depth for January 2019. The temperature was originally recorded at approximately 15-min intervals compared to the mean average temperature for the day (red line), mean average temperature for the ISO week (blue line) and mean average temperature for the month (green line). A) shows temperatures for January. The light shaded area shows the week extracted for B, and the dark shaded area shows the day extracted for C. B) Temperatures for Week 3 witch each panel representing a day (14th – 20th January), C) Temperatures on 18th January. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

guidance and standardization, farms may record temperatures at different depths, which would affect comparisons between sites. In this study, the BarentsWatch temperature data was used with a certain level of confidence as the regulatory requirements state temperatures reported to BarentsWatch must be taken at 3 m depth (Norwegian Directorate of Fisheries, 2012). However, while at least weekly measurements are required by the regulation, there are no requirements or guidelines for when the measurement is to be done, e.g., the time of the day, or how to aggregate and report multiple or continuous measurements done over a week. We also acknowledge the scope for potential errors regarding the exact placement, calibration and maintenance of the sensor, which could affect the precision and accuracy of the results. As climate change assessments require monitoring of conditions over very long time periods (decades), data users also need to remember that technology will change over time with new and different sensing equipment that could affect some analysis and the interpretation of results. Discussions with industry are essential to ensure data is being used in a responsible manner whether it is in climate change assessments or for other purposes. As data platforms become more popular and offer more data, it may be useful to have arenas associated with the platform (e.g., workshops, webinars, forums) to discuss challenges, limitations, opportunities and needs on all sides.

Temperatures in the cages vary throughout the day, as highlighted with the example from Farm B and documented in other studies (Johansson et al., 2009; Johansson et al., 2006), therefore a weekly average based on temperatures taken at a single point of the day is not directly comparable to a weekly average based on temperatures taken, for example, every 15 min. Likewise, as shown in this study with Farm B and other studies (Sampaio et al., 2021), averages may mask conditions that the fish are exposed to, which may affect any subsequent analysis. Fixed requirements and common protocols are essential for usability of open data (Reichman et al., 2011), and this includes ensuring consistency in data collection and reporting. Standardization in the precision of reported data would improve usability (Staines et al., 2022) and allow for comparisons between farms and weeks. Standardised procedures and consistent metadata would improve the usability and interpretation of the open data. Discussions are needed to develop the protocols and determine the frequency of data collection and reporting, including the numerical precision for reporting (i.e. number of decimal places). In 2022 a Norwegian Standard addressing the terminology and methods for documentation of Atlantic salmon and rainbow trout production (NS 9417 © Standards Norway, 2022) requires the implementation of an extended temperature monitoring programme in differing aquaculture production systems and states that temperature in marine net cages should be documented at 3 m, 5 m, 15 m, and also, the maximum cage depth in the middle of the cage (NS 9417 © Standards Norway, 2022). AquaCloud (aquacloud.ai), a data project designed to address and combat Norwegian aquaculture challenges related to e.g., environmental monitoring, has created a sensor data standard (https://aquacloud.ai/sensor-data/) to facilitate the collection, auditing, processing and sharing of environmental data including temperature. It is also working on environmental data standards to establish an industry standard for net cage environmental data collection in accordance with NS 9417 (see https://aquacloud.ai/environmental-data/). If used consistently across the industry, then data standards and common protocols enhance the usability of recorded data for other purposes such as climate change assessments.

It is important that end-users understand what data on open platforms can be used for, acknowledge limitations, and appreciate the wider context to the data. As data on open platforms can be accessed and used by anyone, with no prerequisite of specific aquaculture knowledge, there may be a need to provide more contextual information to avoid misunderstandings. This is important for climate change assessments which seek to establish potential impacts and recommend adaptation strategies, as conclusions based on misinterpretations could lead to suboptimal decisions or maladaptation (Barnett and O'Neill, 2010; Reckien et al., 2023). In the case of aquaculture, analysis and interpretation within a climate change context should consider the farming environment in which the species occupy and how they behave. It has been well established that temperature and temperature preferences are a major driver for how fish distribute themselves within a cage (Oppedal et al., 2011) and this distribution can either be due to the fish selecting a preferred temperature within a given range or gradient, or due to the fish actively avoiding temperatures that are unfavourable or outside their tolerance range. Though it is difficult to integrate this level of information into future projections of climate change, it is important to acknowledge that the fish experience the real-time conditions and not long-term averages, and this study has shown that differences between real-time conditions (e.g., 15 minutes) and weekly and monthly averages can be considerable as several degrees can have major consequences for the fish. Datasets such as BarentsWatch can provide better understanding of the conditions experienced by the fish, as well as variability between sites and over time, and this can provide important context for climate change impact assessments and lead to more robust suggestions for adaptation planning.

As noted above, the required weekly monitoring and reporting of sea temperatures at 3 m is a starting point for understanding conditions within a farm, but data from other depths and more frequent observations are required to understand the variable conditions that occur within cages and the extent to which they can drive the health and welfare status of the fish within each rearing system (Johansson et al., 2009; Johansson et al., 2006; Oppedal et al., 2011; Noble et al., 2018). Reporting temperatures at a variety of depths and locations, in and around where the fish are, can therefore provide end users with valuable information of how the water environment can influence spatio-temporal fish distribution patterns (Noble et al., 2018). Such data can also be used to identify spatio-temporal periods and locations where temperature gradients within a cage can put fish health and welfare at potential risk, and this information can be used to shape both short- and long-term husbandry planning and decisions. At present, it is not possible to integrate high frequency environmental monitoring at multiple depths for every farm location within an online open data platform like BarentsWatch, however some guidance on interpretation of the data could be included to enhance responsible use of the data.

Many salmon farms are moving more towards automated data collection via sensors (O'Donncha and Grant, 2019) and this has increased the availability of data that can be used to better understand the range of spatio-temporal conditions that fish are exposed to. However, the increasing and accelerating variety (data type), volume (data size) and velocity (production and processing speed) of data, as well as questions over veracity (data quality and reliability) and value (worth of data), create many data management challenges (Assunção et al., 2015). The variety and volume of data that can be uploaded to, and hosted on, accessible online data portals is limited by many factors such as available resources, technological challenges, data storage constraints, and security concerns (Hashem et al., 2015). Platforms such as BarentsWatch will not contain all the data collected at farm-level and end-users such as climate change researchers need to be aware of this. This is exemplified with Farm A, where at some times of the year, the recorded temperatures had differences of 2 to 4 degrees depending on whether considering 3 m depth (the depth available in BarentsWatch) or 12 m depth (not available in BarentsWatch). Likewise, Farm B shows that end-users need to consider how they would use averages over time and what limitations there may be, and this also has implications for use of future climate projections (Falconer et al., 2023). Hence, when data is being repurposed for a new application such as climate change assessments, researchers should work with industry to better understand what the data that is available can be used for, and discuss other important considerations that may be needed to put any analysis and data interpretation into context, and ensure responsible use of the data.

There were large data gaps when individual farms were not stocked (the dataset had a column "*Probably_no_fish*") or not recording data, and this affects overall usability of the data for climate change studies as long-term continuous datasets are needed for analysis (Falconer et al., 2020; Falconer et al., 2023). Furthermore, incomplete datasets or infrequent sampling times may miss important extreme events such as marine heatwaves (Oliver et al., 2018). Modelling approaches relying on data from the nearest active neighbouring farms and other complementary data sources could potentially serve to fill the gaps, with some uncertainty. More frequent data and continual monitoring of variables such as temperature, even when fish are not stocked in the farms, would be useful for climate change assessments, as has already been highlighted in other studies (Falconer et al., 2020, Falconer et al., 2023).

Unlocking additional value from datasets is one of the key drivers in the move towards open and easily accessible data from authorities and research funding organizations (Janssen et al., 2012), but aquaculture producers are businesses, and they are not subject to the same open-data obligations as the public sector. Ignoring potential commercial sensitivity issues, data collection and reporting is time consuming and can require considerable resources and infrastructure. Though digitalisation is opening up new opportunities for the sector, purchasing, deploying and maintaining sensors at farm sites is expensive and still involves manual labour. Once in the water, sensors need regular checks to ensure they are working properly, for example, the accumulation of biofouling organisms on sensors in the marine environment is a serious challenge that affects their accuracy, functionality, and longevity (Parra et al., 2018; Bloecher et al., 2021). Therefore, the benefits or incentives for data sharing should be clear if farmers are to go beyond regulatory requirements (McGhee et al., 2019). However, some of the improvements may be relatively simple, such as clearer guidance on the level of precision for reported values (e.g., how many decimal places to record values). From this study it is clear that there is huge potential to use the BarentsWatch data for climate change assessments, but there is also a need for more dialogue between industry, researchers, and regulators so that all groups understand the opportunities and challenges in collecting, delivering and using in-situ data to gain better understanding of how climate change is affecting the marine environment and the impacts on aquaculture and other coastal users.

Though the focus of this study was temperature, BarentsWatch also contains other important information, such as disease occurrence and treatments. This data could also have value in understanding how climate change is, and could, affect the sector. For example, understanding trends in temperature associated disease outbreaks (Stene et al., 2014), and then monitoring incidences could be used in risk management. Whilst, more broadly, disease outbreaks in new areas could be an indicator that conditions have changed to a new state, and there may be impacts on other aspects of the ecosystem. Sentinel species are used as early warning systems, alerting humans of potential risks or dangers ahead (Hazen et al., 2019; Orth et al., 2017) and the most famous example of their use is the canary in the coal mine. Since farmers monitor environmental conditions and biological responses, there may be potential for aquaculture sites to act as sentinel systems with regard to both their environmental circumstances and disease situation. However, confidence in the data is essential as any analysis is dependent on good quality data. Further, disease outbreaks are often multi-factorial (Boerlage et al., 2020), and this, including preventative or control measures (Overton et al., 2019), could mask environmental changes.

There are many challenges in developing national-scale data platforms (Meyer et al., 2020; Wysel et al., 2021) and the BarentsWatch platform is one of the most advanced open access data platforms in the aquaculture sector. BarentsWatch has had huge investments (https://www.regjeringen.no/no/aktuelt/styrker-satsingen-pa-barentswatch/id2885085/) and is well resourced since it supports several different marine industries, including aquaculture. However, data can still be made available for download without a fully operational interactive data platform. Though some companies and organizations may share data voluntary, a well-defined regulatory requirement for data collection and sharing is a powerful mechanism (Kebede et al., 2024), and this is the main reason for the huge amount of sea temperature data within the sea lice monitoring section of the BarentsWatch platform. Examples of good practice of standardised data collection via regulatory requirements or incentives such as certification must be highlighted to encourage more data collection within the aquaculture sector. At the same time, putting too many demands on aquaculture companies could be a barrier to data collection and reduce data sharing across the sector, so any requirements must be justified.

This study has focused on salmon, and it is important to acknowledge that salmon is a high-value commodity in comparison to some other species (Henriksson et al., 2021), and producers of other farmed species may not have the same capacity and resources for data collection and sharing at present. In many countries where data is routinely collected, a full-scale data platform may be a long-term ambition, but there will be other routes that have more utility for making this type of data available and accessible. However, it is also important to acknowledge that there are parts of the aquaculture sector where data collection is limited (Kebede et al., 2024). Furthermore, there are often concerns about making data publicly available, so there is a need for more demonstrable examples of how data sharing can benefit the aquaculture sector.

The findings in this study suggest it would be useful to have a wider discussion on the needs and uses of coastal data amongst all stakeholders and potential data providers, including the aquaculture sector, to determine what is desired and what is feasible. Data is urgently required since climate change is occurring at an unprecedented rate (IPCC, 2021) but there are still huge knowledge gaps on how the local environment is changing and how this will affect the aquaculture sector and other activities in most coastal areas (Falconer et al., 2022). At present, the temperature data within BarentsWatch cannot be used for robust climate assessments due to the lack of standardization. However, if the temperature data was in a more accurate, precise, and comparable format then it could be used to analyse trends and anomalies, which is important to identify rates of change, including seasonal differences, and variability between locations. Long-term records of continuous temperature data are also essential to identify extreme events such as marine heatwaves and cold spells. Hence, the more robust, long-term continuous data that is available, the more targeted and refined climate change assessments can be for specific locations.

5. Conclusion

This study has shown that marine aquaculture has the potential to deliver long-term datasets that are urgently required to understand and analyse changing conditions across coastlines, but more work is required. The positioning of marine fish farms offers an exceptional opportunity to gain detailed information on the rate, magnitude, and variability of climate change in coastal areas. BarentsWatch is a good example of how aquaculture data can be made openly available in near real-time. However, even though BarentsWatch is well supported and resourced, improvements are needed to unlock the full potential of the aquaculture data and their use for understanding changes in coastal conditions. Going forward, improvements in data collection and data processing are needed to improve data quality and consistency. Such improvements must be prioritised as this will increase the utility and usability of the data and generate important knowledge not only for the aquaculture sector, but with the potential for a much greater utility for a broader range of stakeholders. Other countries, or other parts of the aquaculture sector, may not have the same level of resources to develop and maintain a full-scale interactive data platform like BarentsWatch, but data can still be shared in more simple formats. Regardless of the method of data sharing, a data platform, or even a simple database, is only useful if it contains reliable data. Hence, more standardised data collection and reporting is essential across all parts of the aquaculture sector. This study has shown that temperature data, originally collected to conform to a sea-lice health monitoring remit, could have value in monitoring climate change in coastal areas and climate change impact assessments, but improvements are needed. The regulatory requirement to report sea temperatures is the reason for the large volume of sea temperature data within BarentsWatch, and further clarification that specifies data collection requirements would be an important step in facilitating use for climate change assessments, and other uses. Delays in realising the value of this potential data source are lost opportunities to gain important information.

CRediT authorship contribution statement

Lynne Falconer: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Stein Halstensen:** Writing – review & editing, Investigation. **Silje Fiskum Rinø:** Writing – review & editing, Investigation. **Chris Noble:** Writing – review & editing. **Trine Dale:** Writing – review & editing. **René Alvestad:** Writing – review & editing. **Elisabeth Ytteborg:** Writing – review & editing, Writing – original draft, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The BarentsWatch data used within this study are freely available and were obtained from the BarentsWatch platform (https://www.barentswatch.no/). Other data is available on request in an anonymised format.

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