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The importance of calibrating climate change projections to local conditions at aquaculture sites

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ABSTRACT

Future climate projections are usually only available at global or coarse scale and the focus is often on long-term global or regional averages. Though useful to analyse general trends and identify potential risks and opportunities internationally, these resolutions are unable to capture the complexity of coastal areas where aquaculture is located, and poorly represent the environmental variabilities to which cultured organisms are subjected. Consequently, most aquaculture planning and management decisions require information at a much finer scale. If climate projections do not adequately represent conditions experienced at aquaculture sites, potential impacts could be missed, adaptation strategies may be inappropriate, and time and resources could be spent implementing ineffective measures. To demonstrate this, we focus on sea temperature and the production of Atlantic salmon (*Salmo salar*) in Norway, the world's leading salmon producer and a country with a latitudinal range that exemplifies the challenges related to generalization of farming practises. The results show that if coarse resolution climate model temperatures were used directly, then impacts on salmon culture could be severely over or underestimated. For overlapping reference periods, the average daily modelled temperatures at selected sites frequently differed by several degrees, with the largest differences being over 6 °C, when compared to daily average farm measurements. This has serious biological and economic implications as potential risks to production could be underestimated unless corrected. Here two bias-correction techniques were used to calibrate the climate projections to farm scale and shown to more accurately reflect the conditions experienced. The calibrated future projections for RCP4.5 suggest increased temperatures at all sites may require adjustments to existing farm management practices, but the nature and severity of the impact will vary with location. Our research clearly shows that local scale conditions must be considered, using locally resolved climate projections, to develop meaningful adaptation plans to meet the growing demand for seafood in a changing climate.

1. Introduction

Anthropogenic climate change is altering coastal and marine environments throughout the world at an unprecedented rate (Burrows et al., 2011; Deutsch et al., 2015; IPCC, 2014; Riahi et al., 2017). At the same time, the human population is growing and there is increased demand for food, ranging from basic nutritional meals to high value commodities (Godfray et al., 2010). Aquaculture is one of the fastest growing food production sectors in the world and is now responsible for more than half of the global seafood production. It is expected that this sector will be an even more important food resource in the future, due to over-exploited wild fish stocks and reduced land available for agriculture (FAO, 2018). However, future aquaculture production will also be impacted by climate change, affecting contributions to global food supply (Barange et al., 2018; Handisyde et al., 2016; Merino et al., 2012; Soto et al., 2019). Industry and policymakers can develop and implement climate adaptation measures to maximise opportunities and minimise risks (FAO, 2017), but they should be evidence-based, with information on how the environmental changes will affect aquaculture as well as relevant future climate projections.

Climate change impact studies often focus on large scale assessment, based on averages across large spatial and/or temporal resolutions. This is useful to assess the distribution of events such as Harmful Algal Blooms (Townhill, et al., 2018), and a way of identifying potential

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vulnerabilities, risks and opportunities for the global food system and aquaculture related-livelihoods (Handisyde et al., 2017). However, for aquaculture producers, it is the environmental changes at the farm and surrounding area that influence key aspects of production such as growth, feed utilization, product quality, welfare, disease treatment, mortality and environmental impact (Austreng et al., 1987; Handeland et al., 2000; Hvas et al., 2017; Kullgren et al., 2013; Magee et al., 2003; Vargas-Chacoff et al., 2018). Therefore, in addition to broad-scale trends, there is also a need to evaluate conditions experienced by biological organisms (Bates et al., 2018; Helmuth et al., 2014), especially for farmed animals that are unable to move location.

Many climate adaptation measures will be area or farm-specific. At a local level, some production challenges may be alleviated by relatively simple farm-measures including the use of deeper nets, change in stocking strategy and use of different feeds. In other locations, more advanced and technical solutions will be required, such as closed-containment systems or selective breeding programmes to produce more temperature tolerant strains. Although some of these may be developed at a regional or national level, their relevance and effectiveness will depend on the local environment and industry need information on the conditions they will have to adapt to before deciding what action they should take. Some adaptation strategies will take time and resources to develop and implement so the aquaculture industry, and associated stakeholders, need future projections of climate for near- and longer-term periods to allow the industry to identify research needs and incorporate meaningful strategies into their plans. These actions are necessary if the sector is to meet the growing demand for food, contribute to Blue Growth strategies (e.g. European Commission, 2012, 2014) and help countries work towards achieving targets set by the United Nations Sustainable Development Goals (e.g. UN SDG 14) (UN, 2015).

Climate modelling is computationally intensive and requires a considerable amount of time and resources. For marine systems, modelled analyses generally focus on the open ocean, where the variability of physicochemical properties is less than in coastal areas and any changes tend to occur over longer temporal and larger spatial scales (Gunderson et al., 2016). Compared to global models, regional models have better resolved forcing (for example bottom topography and coastline) and process parameterisations, leading to improved modelling of biogeochemical processes (Feser et al., 2011) and improved model results (Skogen et al., 2018). However, due to their nature, environmental conditions can vary considerably along a coastline, and though regional models are an improvement, in most cases they still have a mesoscale spatial resolution of at least several kilometres (Gettleman and Rood, 2016) and are considered coarse scale. Consequently, there is insufficient detail to simulate local-scale changes for coastal bays and fjords where aquaculture production takes place.

Few alternatives to coarse scale models exist for aquaculture production in coastal areas. This presents a challenge for impact assessment and adaptation planning as use of generalised averages across large spatial scales can be misleading. Studies considering the impact of climate change on terrestrial agriculture rarely use global model outputs directly because errors in the simulations relative to historical observations are large and the spatial resolution is generally too coarse to satisfy the requirements for finer-scale impact studies (Ramirez-Villegas et al., 2013). Agricultural studies often use bias correction techniques to downscale model outputs to local-scale and correct differences between observations and simulations (Hawkins et al., 2013). Similar correction techniques should also be applied to models used for aquaculture and other coastal studies, particularly as marine species are more vulnerable to warming than terrestrial ones (Pinsky et al., 2019).

The aim of this study is to evaluate the use of a coarse scale climate model to simulate sea surface temperature conditions at coastal farm sites and investigate two bias correction methods to calibrate model projections to local scale. Norway is the world's leading producer of Atlantic salmon (*Salmo salar*) and farms are spread across the fjords, bays and islands along the entire coastline (Fig. 1), which has been

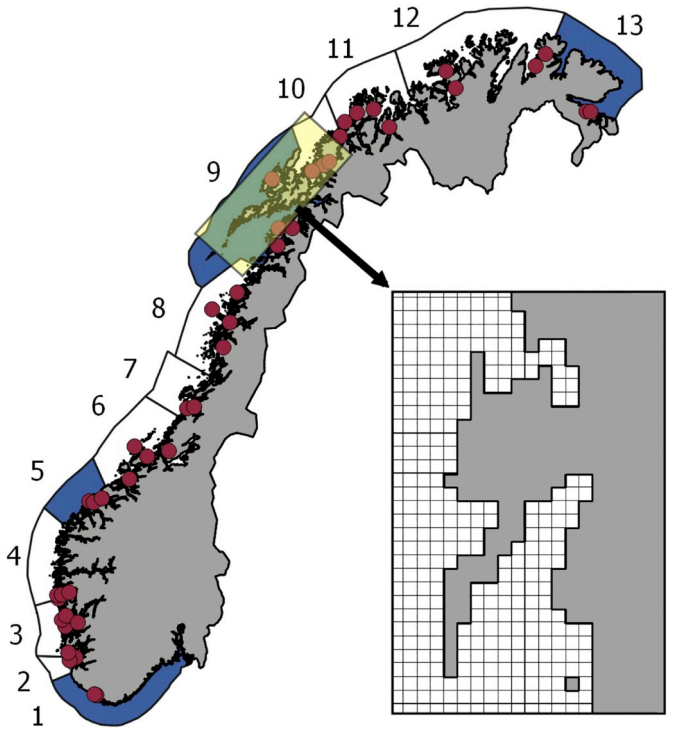

Fig. 1. Map of Norway showing the aquaculture production regions (numbered 1 to 13) extending over the entire coastline. The red dots indicate locations of salmon sites used in this study. Regions 1, 5, 9 and 13 are highlighted in blue as these are the locations where Sites 2, 15, 26 and 42 are located respectively. The box highlights the resolution (each cell represents approximately 11 km) of the NorESM-ROMS climate model downscaling for RCP4.5 for Region 9. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

divided into 13 production regions (Kristoffersen et al., 2018). The latitudinal range extends across 13° latitude from 58°N to 71°N, so the environmental conditions vary greatly, pushing the thermal tolerance of the fish and influencing aquaculture production (Handeland et al., 2000; Thyholdt, 2014). Due to the large number of farms, wide latitudinal range and large amount of data collected by the industry, salmon farming in Norway is an appropriate case study to assess coarse scale climate model projections for coastal aquaculture. To do this, we compiled an extensive dataset of daily measured temperatures from salmon farms in all 13 production regions in Norway. These farm data were compared to temperatures from one of the highest resolution regional downscaled climate models available for the area (Skogen et al., 2018) and then bias corrected to adjust the climate projections for local conditions. Though this study focuses on temperature as an example, it is also relevant to other climate variables. Furthermore, the findings are applicable for all types of aquaculture, including freshwater, as well as coastal fisheries and other aquatic activities. We demonstrate that climate model outputs must be evaluated against and calibrated to local conditions to be relevant for many aquaculture planning and management decisions, climate change impact assessment and climate adaptation strategies. Otherwise, adaptation plans and measures may not be appropriate or effective and may even be unintentionally misleading.

2. Materials and methods

2.1. Measured and modelled temperature data

Daily temperature measurements at marine cage sites were obtained from salmon producers for over 100 farms in Norway. Salmon farms are stocked at different times of the year and their production cycles last

between 14 and 24 months, followed by a period of fallowing when the cages are empty. The datasets therefore covered different periods of time for each farm and as most companies only record temperatures when fish are in cages, there were gaps in the time-series when not stocked. Each dataset was screened to determine suitability for use and processed to remove noticeable errors. Farms with less than four years of data were discarded as the time period was considered too short and not suitable for use in bias correction.

Data availability varied considerably between and within the regions, largely due to the number of farms actively producing fish, and willingness of companies to share data. Four farms per region were considered an appropriate number to use for this study, however in some regions it was not possible to obtain data over at least four years for four individual farms. In total, temperature data for 43 farms were used for varying periods between 2007 and 2017 (Supporting Information, Table S1). Temperature decreases with depth, but salmon do not remain in one constant position within the cage as their depth preferences vary depending on multiple factors (Føre et al., 2013; Bui et al., 2016). Consequently, following discussions with salmon producers, to enable a more robust comparison between modelled temperatures and farm observations, and avoiding thermal fluctuations in the upper few metres of the water column, measured temperatures at approximately 7 m depth were used for this study.

Temperature projections for 7 m depth were extracted from a regional downscaling of the IPCC Representative Concentration Pathway (RCP) 4.5 scenario simulated by the Norwegian Earth System Model (NorESM) (Bentsen et al., 2012; Iversen et al., 2013). Climate model scenarios are used to simulate possible future climate based on potential future greenhouse gas concentrations, emissions and land use changes (van Vuuren et al., 2011; O'Neill et al., 2016). They represent possible developments rather than absolute forecasts (van Vuuren et al., 2011). RCP4.5 is a mitigation scenario that assumes radiative forcing will stabilise at 4.5 $W\,m^{-2}$ (approximately 650 ppm CO_2 equivalent), without overshoot, in the year 2100 due to the reductions in greenhouse gas emissions, possibly through energy policies which move away from fossil fuels, and changes in land use such as reduced cropland and implementation of reforestation programmes (Thomson et al., 2011; van Vuuren et al., 2011). The NorESM-ROMS model RCP4.5 downscaling covers the North Atlantic for 2006–2070 (Skogen et al., 2018) and is among the highest resolution regional climate model simulations available for the study area. However, the horizontal resolution of the NorESM-ROMS downscaling is approximately 11 km, so it does not fully represent the complexity of the topography, coastline (Fig. 1) and physical processes. Projected temperatures were extracted as 5-day averages from grid locations that the aquaculture sites were either located in or near to. The 5-day averages were interpolated to daily in R (R Core Team, 2016) using the 'imputeTS' package (Moritz, 2018; Moritz and Bartz-Beielstein, 2017).

2.2. Comparison of farm measurements and uncorrected modelled temperatures

The uncorrected modelled temperatures were compared to farm measurements to evaluate if direct model outputs could be used in climate change impact assessment and adaptation planning. Statistical comparison was not appropriate as the farm measurements were not continuous, and the NorESM-ROMS data were 5-day averages which were interpolated to daily values. The averaging reduces extremes in the data set. Thus, descriptive and visual comparisons are used instead. It is important to note that climate models do not simulate specific years but generate environmental conditions representative of the modelled (2006–2070) time-period where an individual year (e.g. 2015) does not simulate the actual temperatures of that year, but rather a 'typical' year for that time. Thus, when comparing present day conditions, the uncorrected modelled temperatures represent more general conditions, whereas the measured temperatures show actual conditions and exhibit more day-to-day variation.

Table 1
Relevant temperature thresholds for salmon production.

Temperature	Implications for salmon[a]
> 20 °C	Growth stops, mortality increases
16 to 20 °C	Reduced welfare, reduced food intake, growth slows, increased stress and increased mortality.
14 to 16 °C	Sub-optimal growth, higher risk of reduced health and welfare
11 to 14 °C	Optimal growth, feed intake
7 to 11 °C	Sub-optimal growth, higher risk of reduced health and welfare
< 7 °C	Reduced welfare. Food intake is reduced, growth slows, increased stress and increased mortality.

[a] Austreng et al., 1987; Handeland et al., 2000; Hvas et al., 2017; Kullgren et al., 2013; Magee et al., 2003; Vargas-Chacoff et al., 2018.

For each site, the average daily simulated temperatures at 7 m depth from the NorESM-ROMS downscaling of RCP4.5 (Skogen et al., 2018) were compared to average daily temperatures measured over the same time periods (Supporting Information Table 1) to illustrate the differences throughout a year. There must be some caution on interpretation as there were inconsistent gaps in the farm measurements when data were not collected so, unlike the modelled temperatures, the average farm measurements are not based on a continual time-series. Consequently, the comparison of multi-year average daily temperatures provides an overview of the differences between the modelled temperatures and farm measurements and can be considered a general indicator of how the climate model performs at local-scale and be used to assess variability between sites.

2.3. Bias correction

Differences between observations and climate model outputs are often referred to as biases and can be due to the grid cell resolution, model setup and parameterisation, as well as limitations in understanding of physical processes (Ho et al., 2012; Teutschbein and Seibert, 2012; Gohar et al., 2017). Bias correction uses observed data to calibrate the projections. The bias correction methods described by Hawkins et al. (2013) were used in this study. The first bias correction method (BC1, eq. 1) is a technique where the difference between the observed and simulated temperatures for a recent reference period are calculated and then added to the future climate projection.

$$T_{BC1}(t) = M_{FUT}(t) + (\overline{O_{REF}} - \overline{M_{REF}}) \quad (1)$$

where T is the corrected temperature, M is the modelled projection and O is the observed data. *REF* and *FUT* refer to the reference and future time periods respectively and the bar above a symbol indicates the time mean.

The second bias correction method (BC2, eq. 2) is an extension of the previous, which also considers changes in variance by including standard deviations (Hawkins et al., 2013). The sample standard deviation (s) was used as the datasets for farm observations had some gaps.

$$T_{BC2}(t) = \overline{O_{REF}} + \frac{s(O_{REF})}{s(M_{REF})}(M_{FUT}(t) - \overline{M_{REF}}) \quad (2)$$

3. Results

3.1. Comparison of uncorrected modelled temperatures and farm measurements

As an indicator of the variability between sites, the difference between the average farm measurements and average uncorrected modelled temperatures for all 43 sites, by Region, is shown in Fig. 2. The largest underestimations of the model occurred at two sites (Site 13 in

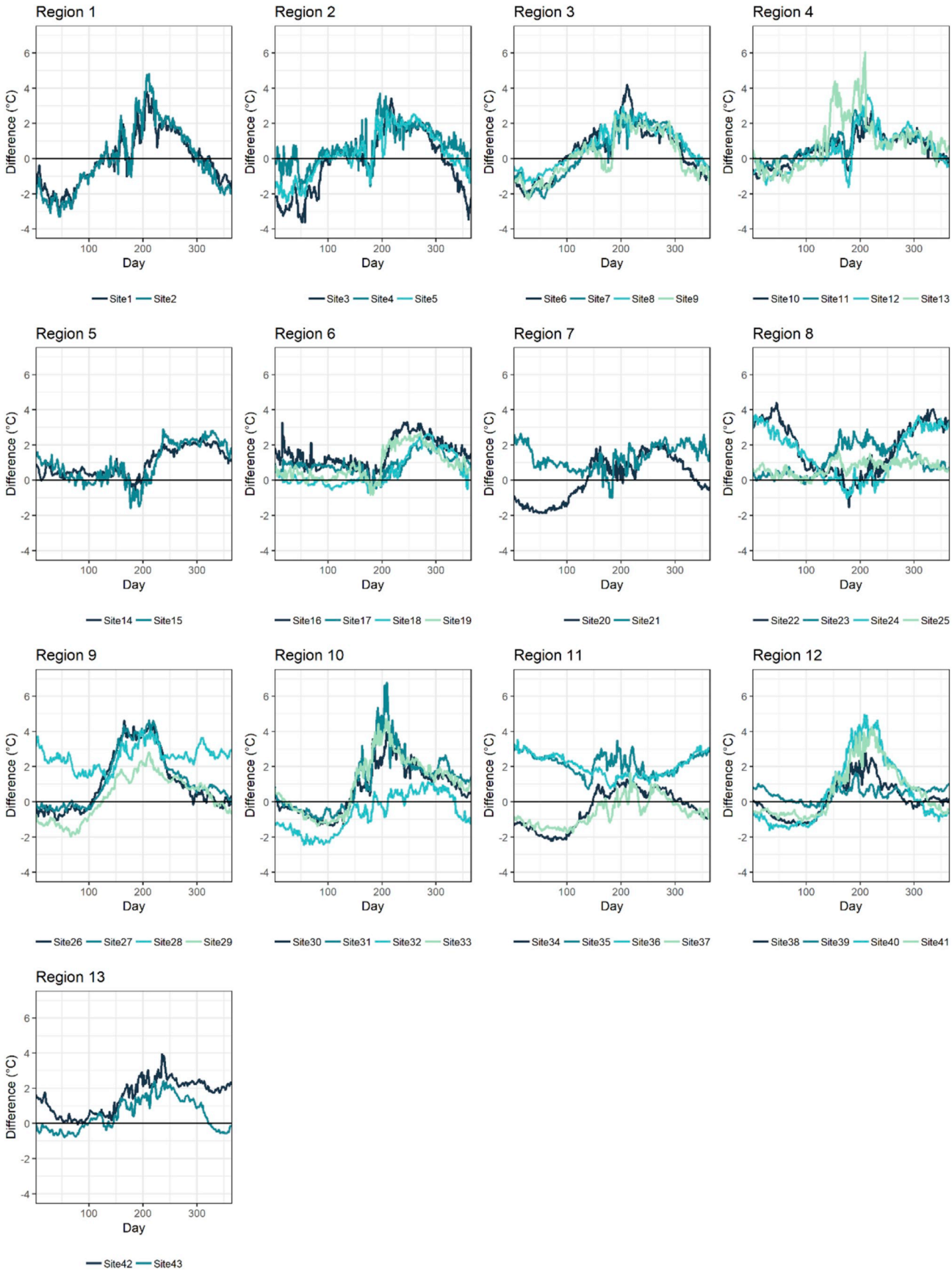

Fig. 2. Difference between the average farm measurements and average uncorrected modelled temperature over the reference period for each site (difference refers to average farm measurement – average modelled temperature).

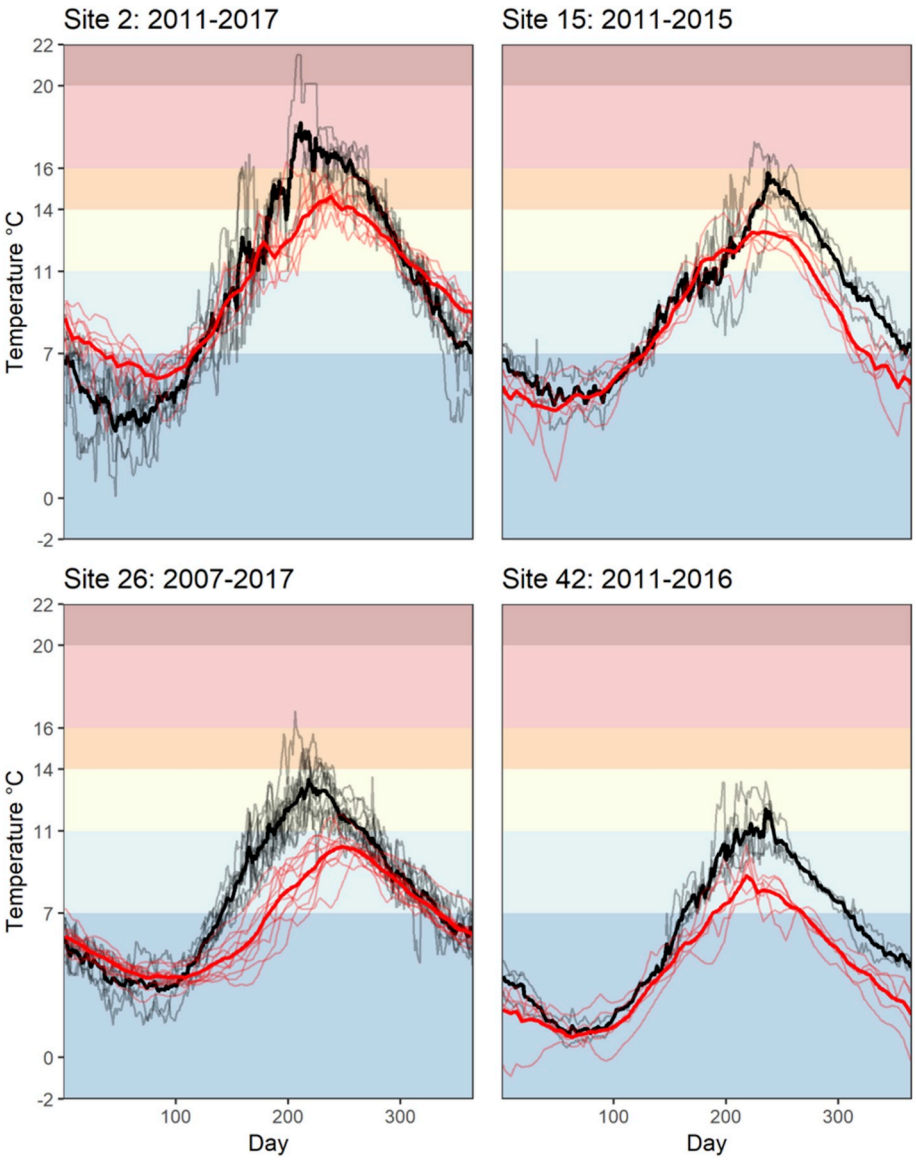

Fig. 3. Model output (red line) and farm measurements (black line) for Site 2, 15, 26 and 42 in Region 1, 5, 9 and 13 respectively. The coloured background denotes relevant temperature ranges and thresholds for salmon aquaculture as outlined in Table 1. The time periods are shown above each panel, the years vary due to the availability of the farm measurements. The thin red and black lines show individual years and the thick red and black line show the averages. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Region 4 and Site 31 in Region 10), where average farm temperatures were > 6 °C higher than the average uncorrected modelled temperatures on at least one occasion. The largest overestimations of the model were at two sites in Region 1 and one in Region 2, where farm temperatures were > 3 °C lower than uncorrected modelled temperatures. It is important to note that Fig. 2 is based on daily averages over several years, and individual years may show more variation and extremes, and differences between farm measurements and uncorrected model outputs may be higher than shown.

Fig. 2 shows there are clear differences between the farm measurements and the uncorrected modelled temperatures. The implications of this for salmon aquaculture are apparent when considered against temperature thresholds, which are indicative of how temperature can influence and affect salmon production (Table 1). Fig. 3 shows sites randomly selected from Regions 1, 5, 9 and 13 to demonstrate the different temperature conditions experienced by farmed salmon across the Norwegian coast (all 43 sites are included in Supporting Information, Fig. S1), within the context of their production thresholds. Site 2 shows that farms in the south of Norway are already experiencing summer temperatures near the upper tolerance range of salmon, but that the model underestimated this potential risk to production by on average 2 to 3 °C, and by up to 6 °C if considering individual years. Conversely, at Site 26 in Region 9, the model also underestimated summer temperatures which were actually within the optimal range for salmon of 11 to 14 °C, and in some years higher, meaning that the climate model misrepresented temperatures that may present potential opportunities for faster growth and possible improved production. At the four randomly selected sites, the model performed better when temperatures were colder, except for Site 2 where winter temperatures were considerably overestimated. Potentially, in this case, missing the health and welfare risks or leading to use of inappropriate feeding strategies. The climate model followed a seasonal pattern similar to those at the sites, although at Site 26 actual temperatures increased earlier in the spring than the model simulated, and at Sites 15 and 42 the farm measured temperatures decreased slightly later than the uncorrected modelled temperatures following the peak summer temperatures.

Generally, for peak temperatures in summer months, the model

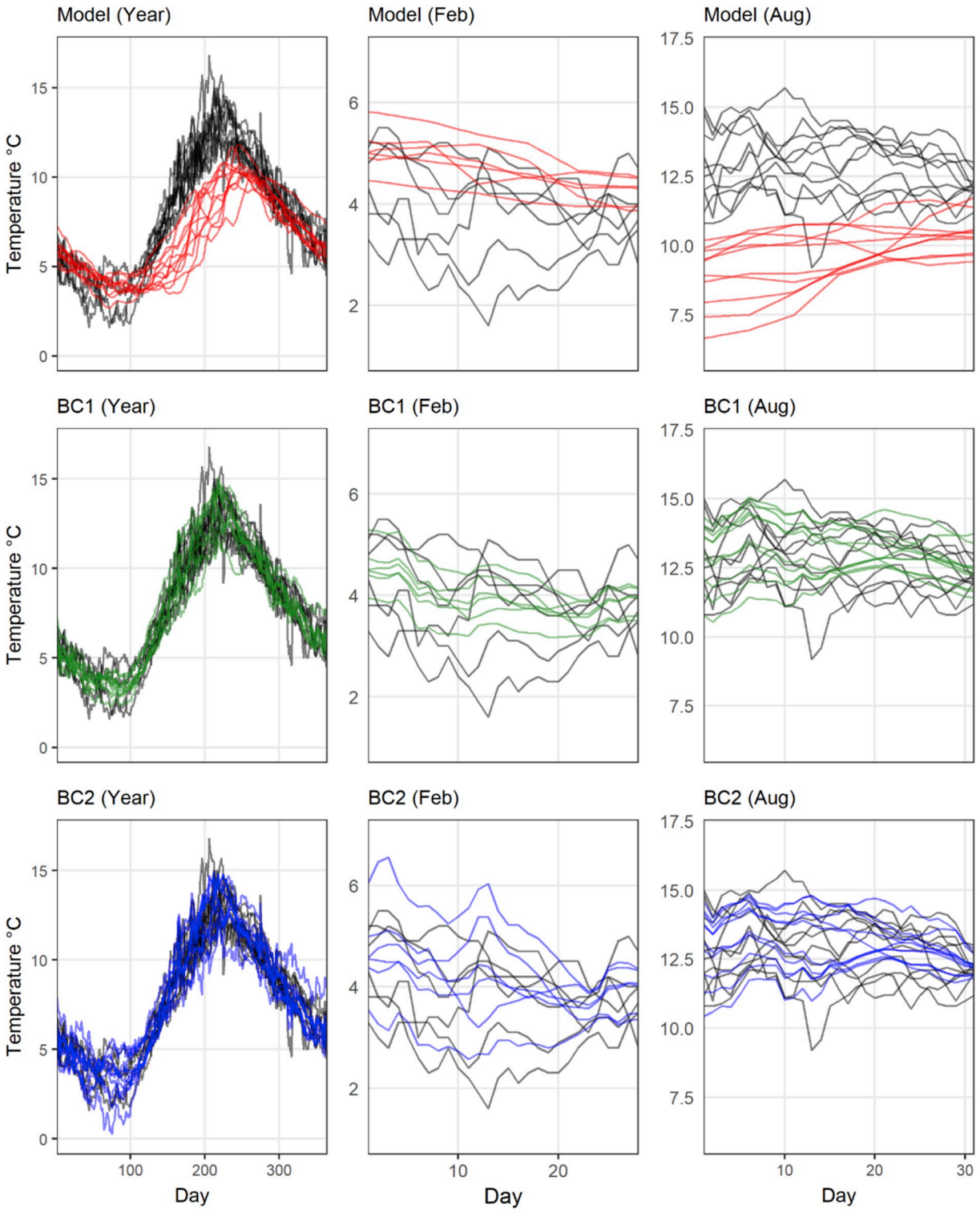

Fig. 4. Comparison of farm measurements (black line) and modelled uncorrected temperatures (red), BC1 (green) and BC2 (blue) for the whole year, February and August at Site 26 in Region 9. The individual lines show different years. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

appeared to underestimate the farm conditions, though the duration and magnitude of difference varied. At other times of the year, it was not possible to establish even simple trends as the model underestimated and overestimated at different sites at different times of the year, even within regions. These results expose the variability between locations and show that a simple common universal or regional adjustment would not be appropriate.

3.2. Comparison of corrected modelled temperatures and farm measurements

Both correction methods improve the projections, so they more accurately reflect the conditions experienced at the farms. This made it possible to calibrate the temperatures throughout the year for all farms, both in winter and summer months, as exemplified for Site 26 (Fig. 4).

The first bias-correction method (BC1) was unable to capture some of the extremes but generally can be considered a good approximation of the average conditions experienced over the reference period. When the uncorrected model overestimated (e.g. February at Site 26) or underestimated (e.g. August at Site 26), BC1 corrected the bias so temperatures were similar to those experienced by the farm. The second method (BC2), accounted for differences in variance, and was also a better match than the original modelled temperatures. The BC2 approach introduced more variation compared to BC1, and on occasion the values were exaggerated. For example, in February at Site 26, some of the bias corrected temperatures were between 0.5 and 1 °C warmer than the actual temperatures experienced in hotter years during the time period for the first half of the month. BC2 is dependent on variance remaining constant over time, so in addition to exaggerating temperatures, it also failed to account for some of the more extreme temperatures. During August there was a single colder year where temperatures fell below 10 °C for several days which was not captured by the model or BCs. Furthermore, the highest farm measurement was 16.8 °C, however the highest BC1 temperature was 15.0 °C and the highest BC2 temperature for the period was 15.0 °C. Although these were improvements on the original model, which had a highest temperature of 11.8 °C, unexpected conditions are not simulated well by climate forecasting models and bias correction can only adjust based on known and consistent variance.

As demonstrated above, the uncorrected model did not sufficiently represent farm-level conditions and there was a bias towards colder temperatures. All sites showed that bias corrected temperatures were more comparable to the farm measurements than the uncorrected model (Supporting Information, Fig. S2).

3.3. Potential effects of warming on aquaculture production

The future temperature projections suggest that for the model, BC1 and BC2 there will be increased temperatures, but the change is neither linear nor consistent. There is also interdecadal variation which may have implications for aquaculture production (Fig. 5). As with previous sections, to illustrate the differences between regions for decades between 2010 and 2069, the four randomly selected sites from Regions 1, 5, 9 and 13 are used as examples. The differences between the two bias correction methods are clear: BC2 shows a greater range of temperatures and for most decades, the cold and hot extremes are greater in BC2 than BC1 or the original uncorrected model, as this approach also considers variance.

At the most southern location, Site 2 in Region 1, BC1 and BC2 show a large number of days when temperatures are above 16 °C, and some days reaching above 20 °C. In the 2020's, some of the highest BC2 temperatures are projected to reach nearly 28 °C on occasion. Temperatures higher than the thermal window for salmon, which will negatively affect production. At Site 15 in Region 5, BC1 and BC2 show increasing temperatures that are likely to affect production, although in the near-future the extremes suggested by BC2 are not projected to be as high as those in Site 2. These results highlight the spatial variability of potential climate change impacts along the Norwegian coastline.

At northern sites, which have temperatures at the lower end of the thermal range for salmon, increased temperatures could be an advantage for growth. At Site 26, both of the BCs show fewer days below 4 °C than at present, particularly in the 2030's and onwards. However, though there may be improved growth, the increased temperatures may also increase the prevalence of disease and parasites which were previously not an issue due to the colder temperature. Therefore, it is important to consider the direct and indirect impacts of temperature change throughout the year and what the implications are for farm management. The BC1 results suggest that Site 42 will still experience colder temperatures in the future, but the upper temperatures will increase so there could be a greater temperature range than currently experienced. BC2 suggests there may be some risks to production with days potentially increasing above 20 °C from 2020 to 2029. Although Site 26 and Site 42 are both in the north of the country, the conditions experienced and potential changes are different. This is due to the locations and latitudinal variation but also local hydrography and topography. Other sites in these regions may also be different.

4. Discussion

There is a clear need for caution when using coarse scale climate model projections for climate change impact assessment on farmed animals and food production. Particularly for farming in coastal and marine environments, since health and welfare of cultured animals are driven by temperature and other local environmental conditions. The downscaled NorESM-ROMS for RCP4.5 (Skogen et al., 2018) is among the highest resolution climate model simulations available for the Norwegian coastline. However, it is still too coarse to fully capture the conditions experienced at salmon farms. The implications of using uncorrected coarse scale modelled temperatures are highlighted in this study. The results show the climate model underestimated summer temperatures at each of the 43 sites compared, often by several degrees. This could have biological and economic consequences for cultured fish and producers as potential risks to health and welfare could be underestimated, adaptation plans may be inappropriate, and time and money could be spent implementing ineffective measures.

The uncorrected modelled temperatures generally followed the same seasonal pattern as those experienced by the farms, but at some locations the spring increase and autumn decrease of temperatures were out of synchronisation by several weeks. As with other food production sectors which rely on overall global ecosystem health and function (Stevenson et al., 2015), the timing of seasonal changes is important for the aquaculture industry, and reliable information is needed as it influences many important aspects of production from stocking strategies to product quality (Mørkøre and Rørvik, 2001). If climate change impacts on seasonal changes in the environment and biology are ignored or not appropriately represented by climate models, then contributions to food security may be compromised, with wider implications for biodiversity and human health (Stevenson et al., 2015).

While some differences between models and reality are expected, the results of this study demonstrate that the differences are large enough to have considerable implications if the uncorrected temperatures were used for impact assessment or adaptation plans. Coarse scale climate models are not designed to be applied at local level, but in the absence of alternatives, and a need to understand how the environment may change, methods such as bias correction can provide improved projections at local sites. Consequently, it is recommended that based on the results from this study, aquaculture should follow agriculture (Hawkins et al., 2013) and use bias correction techniques to calibrate coarse model outputs to local scale. Nevertheless, it must be acknowledged that bias correction can introduce additional uncertainties. One of the issues with bias correction is the assumption that the magnitude of difference between modelled projections and observed data will be consistent into the future (Ehret et al., 2012; Maraun, 2016). Another potential limitation is the availability and quality of farm measurements. Recent observations should be used but even for the relatively advanced salmon aquaculture industry, there is a lack of continuous time series data on environmental conditions as companies usually only keep records when a site is stocked. Here, the importance of such data for climate change assessment has been demonstrated, and the approaches would be strengthened with more and continuous farm-level data. Long-term monitoring and data collection programmes that are supported and/or implemented by industry are vital to understanding how the environment is changing and the implications this has for aquaculture production (FAO, 2017; Soto et al., 2019).

All sites assessed showed that bias correction was an improvement on the original model projections. Other correction and downscaling techniques exist (Tabor and Williams, 2010; Teutschbein and Seibert, 2012; Räisänen and Räty, 2013), and may show different results, but

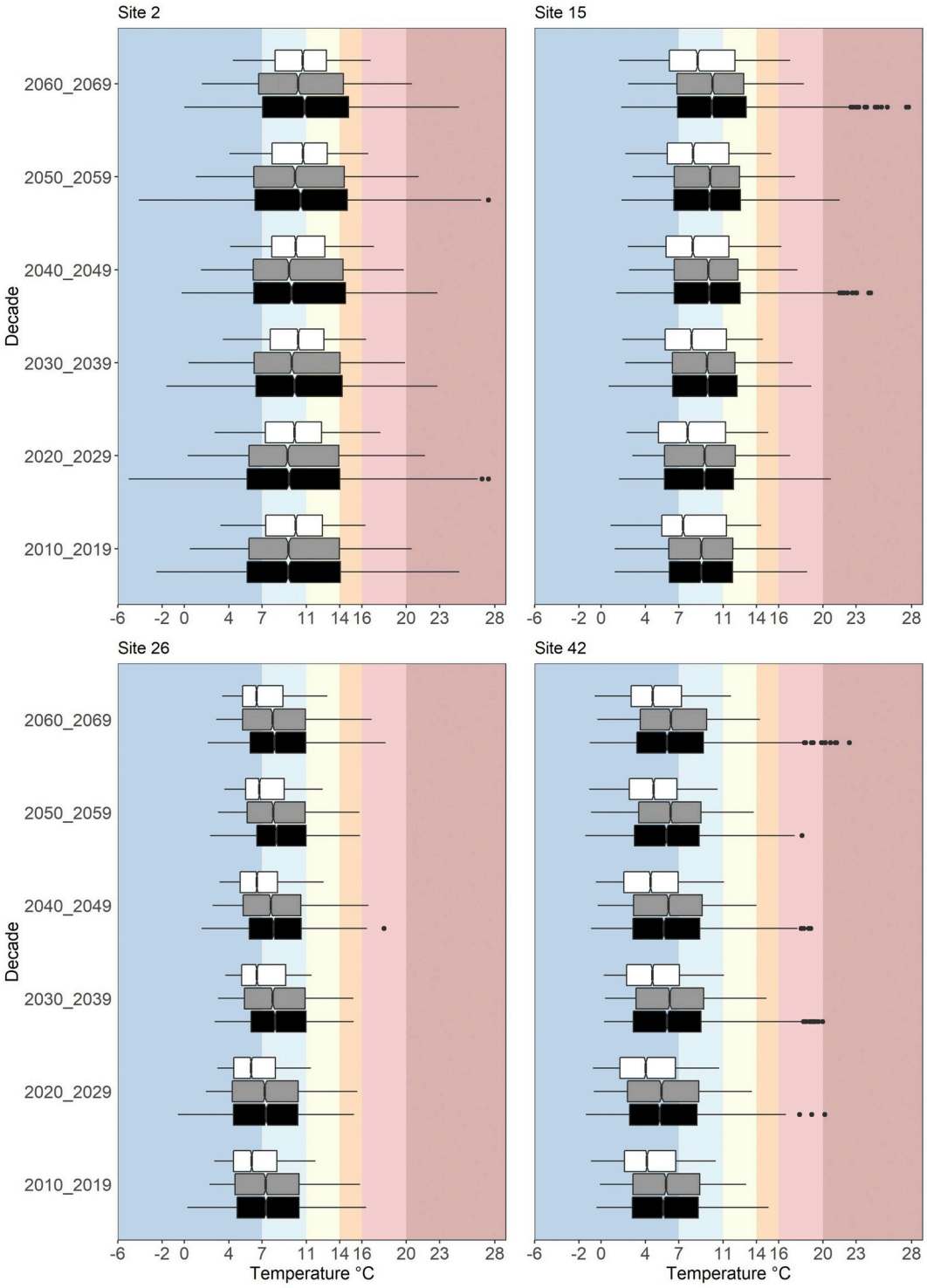

Fig. 5. Boxplots showing the distribution of modelled temperatures for the uncorrected model (white), BC1 (grey) and BC2 (black) for each decade. The coloured background denotes relevant temperature ranges and thresholds for salmon aquaculture outlined in Table 1.

the two methods evaluated here are considered appropriate as the corrected temperatures are comparable to the farm measurements. BC1 represents the average conditions well, but may underestimate the more extreme years, while BC2 simulates variation which may or may not be experienced at the sites. The results will be influenced by the number of years used for bias correction. BC2 is particularly sensitive to the amount of data used and is only appropriate if there is farm data over at least four or five years. Clearly, there are advantages and disadvantages to both approaches for assessing potential impacts of climate change on aquaculture and other coastal activities. However, the choice of method will depend on the scope of the work and the availability of observed data and modelled projections. Since the differences between model and reality varied considerably depending on the site, it would not be appropriate to use one correction factor for the entire country and in most cases even a regional-based correction factor would not be suitable and individual farm-scale corrections are required.

The bias corrected temperatures show that future aquaculture

production in Norway will be affected by increasing temperatures due to climate change, and that there are different implications, depending on the location. Southern sites in Norway already experience temperatures that are higher than optimal during summer months, and the bias corrected models suggest days above 20 °C would increase in coming years. BC2 suggests that some sites could be experiencing temperatures so high that they would pose considerable risk to production. In all regions, farm management strategies and feed composition may have to adjust to changes in temperature affecting feed utilization, metabolism and growth (Handeland et al., 2000).

The analysis focused on daily temperature which is an important time-step for many decisions in aquaculture and the information can be used to evaluate how production may change in the future, for example temperature projections can be used in bioenergetic models to simulate potential growth of farmed fish (Stavrakidis-Zachou et al., 2019) and identify possible risks and opportunities between farm locations. Other stakeholders may not have such information, but bias correction could also be used for monthly, seasonal or even yearly analysis. Regardless of time-step, if using modelled temperatures to inform climate adaptation measures, it is important to evaluate if the modelled temperature can sufficiently represent observed temperatures as a difference of several degrees (whether daily, monthly or annual average) could have important implications for decision-making and adaptation planning.

It is important to stress that the temperature projections used in this assessment are one single realisation of an intermediate climate change scenario (Skogen et al., 2018; van Vuuren et al., 2011). RCP 4.5 is used here as an example to demonstrate the issue of scale between climate models and local environments, but it is not a fixed pathway and it is only one of a range of scenarios which explore different trajectories of greenhouse gas concentrations, leading to alternative futures with different magnitudes of climate change (van Vuuren et al., 2011). Climate change impact assessment and adaptation plans should consider multiple scenarios to assist decision-makers. Whether different actions are taken or not by the global community, the consequences for the future climate will change accordingly, as time progresses. Thus, scenarios may become outdated and targets, such as those set in the Paris Climate Agreement (UNFCCC, 2015), may need to be revised. Consequently, new scenarios and updated projections (O'Neill et al., 2016) should be used for aquaculture when available and impact assessments and adaptation plans should be regularly evaluated and updated in response to the changing environment, new information and models. The bias correction techniques demonstrated here can and should be used for other climate models and scenarios to ensure they too are relevant for local scale assessment.

The 43 sites, across the 13 salmon production regions, covered a wide variety of geographical locations, over a large latitudinal range. The farm measurements demonstrate the variability of environmental conditions between sites, confirming the need for local assessment as broad, regional or national generalisations will miss the environmental sensitivities that are important for farmed species in aquaculture production areas throughout the world. Furthermore, if climate models are used for impact assessment and adaptation plans then it is important to acknowledge the limitations and knowledge gaps. This includes the scale issues that have been highlighted here, but also uncertainties surrounding the magnitude and frequency of rare events (Ragone et al., 2018), such as prolonged periods of extreme warming. These events present risks to aquaculture production (Wade et al., 2019) as well as to the wider marine ecosystem and other coastal activities (Caputi et al., 2016). However, the occurrence, timing and distribution of rare events are difficult to predict, and climate model analysis and products tend to focus on long-term climate trends rather than relatively short-term events that last days or weeks. Caveats which cover such limitations and knowledge gaps should be included when using climate projections at any spatial resolution to avoid overinterpretation of results or underestimation of risks.

Common climate adaptation strategies encompassing specific production sectors over whole continents are being developed for several species around the world (FAO, 2017). However, as we illustrate in this study, common adaptation strategies are only relevant when discussing overarching issues and general trends, and not particularly useful for many decisions and adaptation measures which will be implemented at a local scale. Our results clearly illustrate the need for appropriate local climate change descriptions to enable the development of adaptation plans that can support sustainable production of seafood into the future. Consequently, to prepare for future climate change, there is an urgent need to implement long-term monitoring and data collection campaigns at aquaculture sites to understand how the environment is changing and, as long as climate model projections at very fine scale (~100 m) are not realistic, then use this data to calibrate models to spatial scales relevant for aquaculture producers. Furthermore, huge knowledge gaps exist related to the temperature thresholds for many aquaculture species, including salmon, especially when it comes to long term effects of sub-optimal conditions and reoccurring high thermal fluctuations. The focus for this study was temperature, since temperature is considered the main abiotic factor for fish physiology (Brett, 1979), but there are other climate change stressors that will directly or indirectly affect production, and it is important to consider combined effects (Sarà et al., 2018) and to develop models that account for these synergies. This is an additional challenge for impact assessment and adaptation planning as each stressor will also exhibit spatial heterogeneity. Ultimately, adaptation measures are only effective if they address the issues that are or will be relevant to the industry and these must be based on climate projections that are appropriate for the area.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aquaculture.2019.734487.

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