Computers and Electronics in Agriculture 218 (2024) 108676

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Review article

Digital Twins in intensive aquaculture — Challenges, opportunities and future prospects

Martin Føre [a,*], Morten Omholt Alver [a], Jo Arve Alfredsen [a], Adil Rasheed [a], Thor Hukkelås [a], Hans V. Bjelland [b], Biao Su [b], Sveinung J. Ohrem [b], Eleni Kelasidi [b], Tomas Norton [c], Nikos Papandroulakis [d]

[a] Department of Engineering Cybernetics, NTNU, Trondheim, Norway
[b] Department of Aquaculture Technology, SINTEF Ocean, Trondheim, Norway
[c] Animal and Human Health Engineering (A2H), KU Leuven, Belgium
[d] Institute of Marine Biology, Biotechnology and Aquaculture, Hellenic Centre of Marine Research, Heraklion Crete, Greece

ARTICLE INFO

Keywords:
Digital twin
Marine fish farming
Precision farming
Modelling

ABSTRACT

Digital Twin technology has emerged to become a key enabling technology in the ongoing transition into Industry 4.0. A Digital Twin is in essence a digital representation of an asset that provides better insight into its dynamics by combining *a priori* knowledge of the system through mathematical models with online data acquired from sensors and instruments deployed in or at the physical asset. While the technology is seeing increased use across several different industrial, governmental and research sectors, and across scientific disciplines, its application within aquaculture is still in its infancy. However, due to the rapid ongoing development in technological methods in aquaculture, an increasing number of the building blocks required to make a Digital Twin for aquaculture purposes are becoming available. We set out to explore these possibilities by first defining a Digital Twin — what components it should contain, how it should be constructed, and outlining the capability levels of a finished Digital Twin.

Our next step was then to explore the state-of-the-art within the different required components and enabling technologies within aquaculture, thereby identifying the current foundation for developing Digital Twin technology in this sector. Following this, we developed concrete case studies that elaborate upon how we by combining existing and developing new technological tools could envision developing Digital Twins for three application areas of high industrial relevance, namely oxygen conditions in sea-cages, fish growth in sea-cages and in-cage robotics and vehicle operations. In conclusion, we present our thoughts on the potential of Digital Twin technology in being a key component in ushering in Industry 4.0 in aquaculture, and outline a pathway on the way onward towards achieving this goal.

1. Introduction

The concept of Digital Twins has gained a strong following, and been proposed as an emerging disruptive technology in several industrial fields (Rasheed et al., 2020). A Digital Twin offers a digital representation of a real-world system or asset of interest that merges mathematical models (knowledge based and data driven models) of that system with real-time data from the system (VanDerHorn and Mahadevan, 2021). By capitalising on the symbiosis of these components, Digital Twins typically offer capabilities within describing and predicting system dynamics, and monitoring and estimating system states that are difficult to observe directly. If elements from decision support and risk analysis are also included, these capabilities may be further expanded to also include the ability to diagnose challenges arising in the system and prescribe/recommend solutions to these. Provided that the Digital Twin's representation of the system/asset is sufficiently complete and computationally tractable, Digital Twins can also be a tool for realising closed-loop autonomous control of the system/asset.

While the capabilities of Digital Twins developed and applied in many fields are increasing rapidly (Rasheed et al., 2020; VanDerHorn and Mahadevan, 2021), there have been few attempts at using Digital Twin technology for aquaculture applications. One of the main reasons for this is probably that intensive aquaculture is a comparatively young industry. Most early R&D efforts in aquaculture have accordingly had to focus on solving the concrete biological challenges of underwater

* Corresponding author.
E-mail address: Martin.fore@ntnu.no (M. Føre).

https://doi.org/10.1016/j.compag.2024.108676
Received 20 September 2023; Received in revised form 19 January 2024; Accepted 23 January 2024
Available online 1 February 2024

animal production. However, many of these challenges have now been overcome, and the industry is at a point where the focus should be shifted to developing farm management practices to better monitor and control the fish production. Developing such new farming practices requires insight into the inner dynamics of the biological and physical processes involved in fish farming, and the ability to continuously monitor these. This is difficult to achieve in aquaculture as one of the major challenges endemic to this industry is that most of the system dynamics occur under water, rendering them difficult to observe and safely access by humans. Digital Twin technology provides a potential solution to this challenge. Considering the current and projected growth of aquaculture, and its expected importance as a future provider of human sustenance, it is important that the potential to create useful Digital Twins for aquaculture is explored, and that a roadmap for achieving this and thus reaping the benefits of doing so, is established.

1.1. Intensive fish farming

Aquaculture is one of the key providers of food for human consumption, and fish farming is believed to be a crucial protein source for the growing world population. This trend is also seen in global numbers for aquaculture finfish production, which increased from 38 to almost 60 million tonnes between 2010 and 2020 (FAO, 2022). Fish farming can roughly be divided into two different production paradigms: extensive and intensive fish farming. While extensive fish farming is mainly based on the natural environment at the site providing for all the needs of the fish, intensive fish farming is focused on actively controlling the culture conditions, feed delivery in particular. Better control leads to improved end product quality, faster growth and more predictable growth trajectories, all of which contribute to a better ability to deliver fish to the market in accordance with customer needs and desires. Better control over rearing conditions also improves the farmer's ability to manage industrial challenges associated with important areas such as fish welfare, Health, Safety and Environment (HSE) and environmental impacts (Føre et al., 2018).

The most common form of intensive fish farming in Europe is cage based farming, where the fish are contained within net enclosures suspended from plastic/polyester collars floating at the surface (McIntosh et al., 2022). Cage based farming has grown rapidly in recent years, both in terms of gross tonnage and local farm scales (McIntosh et al., 2022). For instance, a typical salmon farm may today contain as many as 10–15 cages, each measuring circumferences up to 200 m and depths down to 50 m and containing up to 200 000 individual fish. Although at relative smaller scales, the situation is similar in the Mediterranean Sea with cages of 120–160 m in circumference, depths from 30 to 50 m containing 150 000 to 200 000 individuals. While these numbers and scales are indicative of industrial success, they also impose increased challenges in monitoring the cultured animals during production (Føre et al., 2018). This is an action that is required of any form of animal husbandry, in many countries even by law (Medaas et al., 2021). Moreover, the sheer spatial extent of fish farms limits the ability to monitor all elements of the production system and actively control the production through low-level control actions such as using mechanised feeding systems to deliver feed.

Although the general principles of cage based farming are still similar to that applied decades ago, external processes have stimulated technological development in both farming structures and practices. One such external process was an arrangement recently hosted by the Norwegian government where experimental salmon production permits were offered to companies that wish to develop new production concepts for salmon (Moe Føre et al., 2022). To qualify for these permits, the industry needed to demonstrate that their concept is different from conventional production forms and that it contributes to solving specific industrial challenges such as avoiding parasites or reducing nutrient release to the environment, or can be applied in areas previously unsuitable for fish farming. This has led to the emergence of a myriad of different novel production concepts that all have their particular properties, and distinguish themselves from conventional cage based farming in design, operational aspects or both. In many countries, there are also strong incentives to locate sea-based farming further from shore, both due to conflicting claims from other industries near the coastline, such as capture fisheries and recreation and tourism, and due to the shortage of near-shore sites suitable for fish production (Bjelland et al., 2015; Morro et al., 2022). Furthermore, new systems in the form of multiuse offshore concepts for combined installations for energy harvesting and aquaculture are also gaining interest as a result of EU policies (e.g., Papandroulakis et al., 2017).

Together, these trends steer production forms toward bigger and/or more complex production units (McIntosh et al., 2022; Moe Føre et al., 2022) that are often placed at more inaccessible locations with harsher environments (Morro et al., 2022). Maintaining intensive fish farming as a viable industry also in the future thus calls for new solutions for better monitoring and controlling the biological production in fish farms. These solutions must be founded in technological approaches.

1.2. Precision fish farming meets digital twins

The main intention of proposing the Precision Fish Farming (PFF) concept was to establish a framework for how technology and automation can be introduced into fish farming practices to better cope with present and future challenges (Føre et al., 2018). PFF seeks to link technology and automation principles with the practical aspects of aquaculture operations, and as such serves as a common arena for the worlds of research and industry, and can also be generalised to non-fish aquatic species. Using the framework, researchers can thus communicate their results and findings in a setting that allows industry to better relate these to their needs and challenges, and hence easier adopt them into new solutions in the future. Conversely, PFF can also be used as a tool for industry to communicate their needs and challenges to research communities in a format that is easier to translate into concrete research activities. This dual purpose enables a better harmonisation between technological research and development and how operations are conducted at fish farms, which is of key importance since any new technology needs to be accepted by the farmers who are responsible for day to day farm management.

Industrial operations in aquaculture are complex as they contain biological and technological elements, and are often conducted in submerged and flexible structures in an exposed sea-environment. A key element in PFF has therefore been to devise a system for breaking aquaculture operations down into distinct phases (Fig. 1). This simplifies technology adaptation as it is then possible to fit specific technological solutions with the simpler sub-operations in each phase instead of trying to do so for the entire process at once.

Several scientific studies on technological development towards aquaculture operations have sought to explore the dimensions proposed in PFF. Some of these have expanded along the *Observe* direction in seeking to develop new smart sensors to quantify various properties related to the fish, e.g., by using machine vision to recognise individual fish by automatically analysing their iris (Schraml et al., 2020) or skin dot patterns (Cisar et al., 2021) and also individual or group fish motion (Georgopoulou et al., 2021). Other approaches include those that combine sensors in networks to acquire a more complete picture of the situation in the farm. This has thus far been done for pond culture, either through integrated networks of stationary (Komarudin et al., 2021) or mobile (Ouyang et al., 2021) sensors. Others have proposed to combine sensor data with mathematical models in an Internet of Things (IoT) platform as tools for better *interpretation*, presentation and refinement of the measurement data (O'Donncha and Grant, 2019) or even using satellite data (Chatziantoniou et al., 2022). Modelling was also the focus of the study conducted by Royer et al. (2021) who developed and validated a model describing the oxygen dynamics in a raceway for trout production. More recently, there have been similar

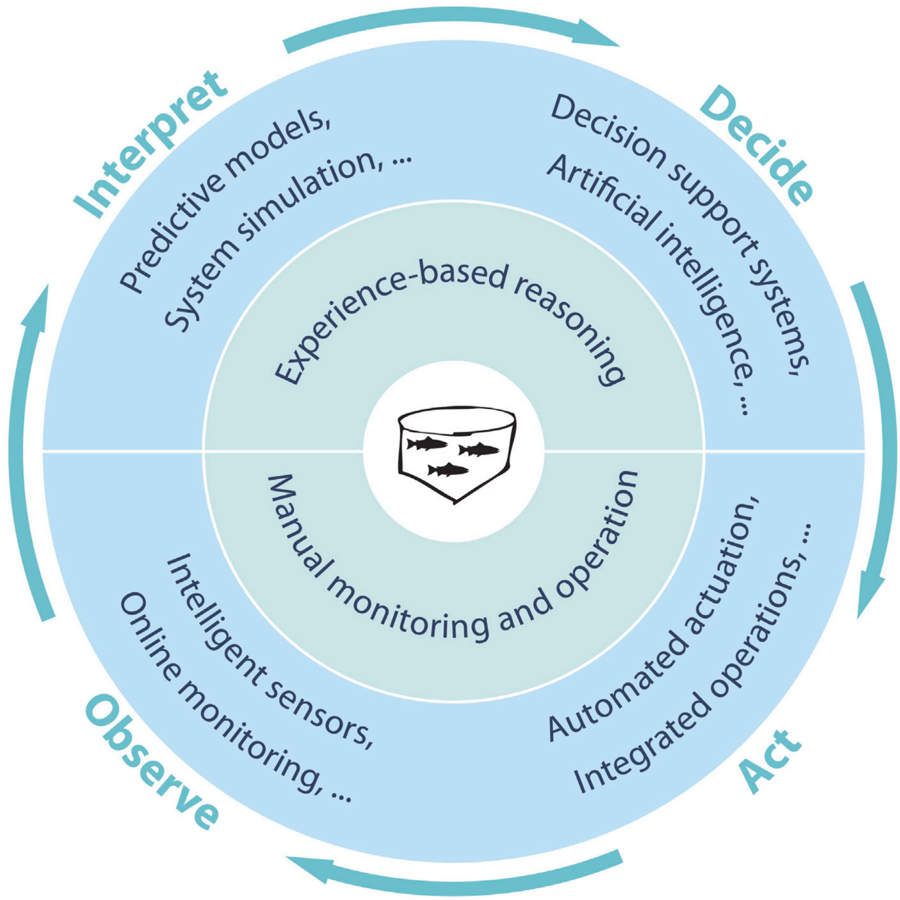

Fig. 1. The Precision Fish Farming concept with the four phases.
Source: Reproduced with permission from Føre et al. (2018).

studies of oxygen dynamics in large ocean based farms (Alver et al., 2022), and that have been used to assess potential effects of cage size on oxygen dynamics (Alver et al., 2023). Although there have been fewer studies targeting the *Decide* and *Act* phases, there are examples where decision support systems have been applied to an aquaculture setting (e.g., Mathisen et al., 2016, 2021), as well as an increasing body of research aimed at aquaculture robotics (Kelasidi and Svendsen, 2022).

These and other ongoing studies illustrate that the PFF approach is being applied either directly or indirectly today. Recent efforts have also taken the next step in seeking to merge the worlds of modelling and instrumentation to better observe and assess structural dynamics at a commercial fish farm Su et al. (2023). However, there have been few concrete attempts at doing similar exercises that also includes the biological processes in aquaculture production units, and most of these have so far been focused on organisms for first-feeding with simple life cycles (Alver et al., 2010) or early life stages in fish. Digital Twin technology could be a key element in serving this need.

Assimilation of real-time sensor data into mathematical models is a core element in the Digital Twin concept, where the aim is to create a virtual representation of a physical asset (Rasheed et al., 2020). Digital Twin technology is being applied within an increasing number of different industrial segments, a trend that has been stimulated by recent advances in enabling technologies such as mathematical modelling, artificial intelligence, and data processing capabilities and visualisation methods. This has also spawned new initiatives aimed at achieving technological convergence between these fields, and since this includes data assimilation into mathematical models, the Digital Twin concept emerges as a natural framework for making the next steps on the path towards closed loop control of fish farming through PFF.

Additional insight into the benefits and opportunities of adapting Digital Twins to animal production can be gained by looking to terrestrial livestock production. The concept Precision Livestock Farming (PLF), which serves a similar purpose for this industry as PFF does in fish farming, was established in the early 2000's (Berckmans, 2017). PLF was founded in the idea that improved control of livestock production (and the benefits thereof) is possible through the intelligent application of technology. This includes the use of sensors to monitor behavioural, physiological and environmental indicators, mathematical models that synthesise existing knowledge on the animal/farm dynamics, and the combination of these to better describe the animal state (production, motivation, stress and wellbeing) under terrestrial farming conditions. Recent advances in fields such as Machine Learning (ML) and Artificial Intelligence (AI) and increased availability of sensors has improved the precision of these applications, and hence their potential applications. This expanded space of opportunities has also spawned an increased interest in the development and application of Digital Twin technology in the agricultural community, particularly to facilitate early identification of issues in animal groups or single animals, as well as assess the impact of these issues (Schleich et al., 2017; Jones et al., 2020). While some recent literature have provided an overview on the possibilities for using Digital Twins in the farm operation management (Verdouw et al., 2021), these are still explorative studies and use-cases focusing on parts of digital twin. Completely integrated Digital Twins have yet to be developed for agriculture mainly due to the inherent diversity in the production systems and complex responses of the animals to their environment and management (Neethirajan and Kemp, 2021). These elements will also be relevant for aquaculture, adding to the challenge of developing Digital Twin technology for this sector.

1.3. Motivation and research questions

The aim of this study was to explore the possibilities and potential challenges of creating Digital Twins for cage based aquaculture in light of the current state-of-the-art, and their potential for future use in fish farming operations. An operational Digital Twin could serve as a platform that:

- Facilitates seamless combination of real-time sensors and predictive models enabling insight into the state and dynamics of the fish population, and potentially projection into the future;
- Is a framework for virtual prototyping of new technologies, operational methods and instruments;
- Can be used to aggregate and operationalise system knowledge, and whose completeness will grow with our increased insight into the system;
- Enables the use of experience gained from one generation of fish farms to develop next generation fish farms;
- Enables real-time visualisation, monitoring and optimal control.
- Supports operations planning at different time horizons by allowing different scenarios to be evaluated;

A successful realisation of a Digital Twin for aquaculture would also open for harvesting the added values of Digital Twins described by Rasheed et al. (2020).

The main research questions we sought to answer in our study were:

1. Is it possible to define a Digital Twin concept for aquaculture applications that enables the exploitation of the advantages of this emerging technology?
2. Which tools and components needed to this end are already available through the current state-of-the-art within aquaculture technology?
3. What are the major knowledge gaps we need to fill to realise Digital Twins in this field?
4. Is it possible through concrete case studies to highlight the way onward toward achieving this goal?

1.4. Methodology and outline of study

Section 2 is largely dedicated to our addressing research question 1. We first surveyed the scientific literature to identify the components required to create a Digital Twin that would fulfil the six roles a digital twin may serve that are listed above.

Searches combining "digital twin" with other keywords including "definition", "challenges" and "values" returned several thousand sources seeking to define a Digital Twin. Since it is very difficult to condense thousands of different approaches into one definition, we thus had to select a set of studies whose concepts had enough common denominators to be feasible to combine. By synthesising the contents from the resulting six studies, we then outlined a possible structure for a Digital Twin for aquaculture, highlighting the different required tools and components.

We also described the different capability levels and concluded our survey of research question 1 by identifying specific applications of Digital Twins in aquaculture and related segments such as agriculture and hydroponics/aquaponics (Section 3.1). This was done through literature searches using "digital twin" together with either "aquaculture"/"fish farming", "agriculture", or "hydroponics"/"aquaponics". While these searches returned thousands of studies, not all of these reflected a full Digital Twin implementation. Of the 13 studies that did, we selected those found most relevant for demonstrating the Digital Twin development and use in these sectors.

Section 3 presents our findings when addressing research question 2, and was thus broken down into subsections targeting each of the main components required to create a Digital Twin for aquaculture. For each component, we first conducted a literature survey where we used keywords that were specific to both the application (“aquaculture” or “fish farming”) and related to the component type (e.g., “sensors”, “computer vision”, “modelling”). We then did the same with a wider application (e.g., “fish monitoring”, “wild fish”, “fisheries”) to also capture publications that were relevant although they were applied to other fields. In cases where the relevant publications exceeded a number that was practical to include in the manuscript, studies were selected based on (1) relevance for the aquaculture industry, (2) the quality of the results, and (3) publication year (newer publications being favoured).

The last two research questions (3 and 4) are largely addressed in Section 4, where we present possible Digital Twin setups for three case studies. The case studies are based on specific industrial challenges in aquaculture we believe can be partly solved through Digital Twin technology. The first of these was aimed at how Digital Twins can improve monitoring of oxygen conditions in sea-cages. This is an increasingly important industrial topic since the intensification of production and increase in farm/cage scale may increase both the risk and consequences of hypoxia events (Remen et al., 2013). In the second case study, the potential of using Digital Twins to get better real-time inputs on fish growth and biomass development in commercial cages was explored. The rationale behind this choice is that biomass development is the supremely most important process in any aquaculture production, and that improved control over this process can have very large impacts in production efficiency and precision. While the first two case studies primarily highlighted the potential of Digital Twins in improving monitoring and control of aquaculture facilities, the third case study was more aimed towards technology development. Recent industrial trends have tended toward increased use of robotics and autonomous vehicles in aquaculture, particularly when considering moving production to less accessible and exposed locations (Bjelland et al., 2015). The third case outlines how a Digital Twin could be used as both a virtual test bench for developing new technologies, and as a monitoring tool during autonomous or remotely piloted vehicle operations in fish farms.

Each study is described by first providing the industrial background and motivation, and then iterating through the main components required to create the Digital Twin. This entails both including existing tools and components that could have a role, and highlighting the knowledge gaps that need to be filled to create the Digital Twin. The case studies also represent potential pathways to developing Digital Twins for aquaculture. In the final conclusion, we provide our thoughts on the current status and future prospects on achieving the vision of acquiring Digital Twins for aquaculture.

2. Defining a digital twin — main properties, necessary components and enabling technologies

Our definition of Digital Twin is in line with those provided by Rasheed et al. (2020) and VanDerHorn and Mahadevan (2021), and the outline of the various properties and elements in Digital Twins will hence be made in accordance with their perspectives.

2.1. Digital twin components

A Digital Twin is defined as a virtual representation of a physical asset enabled through data and simulators for visualising, predicting, monitoring, optimising and controlling system states, and improved decision making (Rasheed et al., 2020). The overarching aims of setting up a Digital Twin may in generic terms be to acquire a tool that enables (1) better real-time remote control, maintenance and optimisation; (2) increased safety in both material and humane aspects; (3) improved knowledge and insight into dynamic processes.

Fig. 2 illustrates the main concepts of Digital Twins, fusing real time monitoring of the system states with mathematical models, and also incorporate some of their main end impacts. This view harmonises with

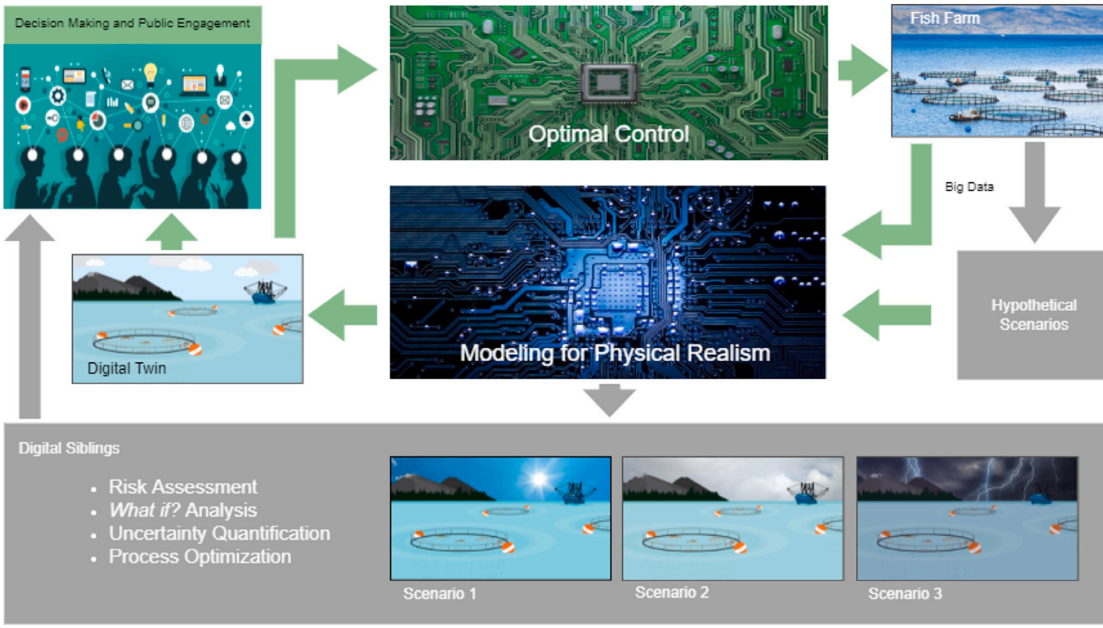

Fig. 2. Conceptual description of a Digital Twin setup.

the Digital Twin concepts proposed within other fields in several other recent studies (San et al., 2021; Elfarri et al., 2023; Stadtmann et al., 2023a,b). The physical asset is here the fish farm (upper right hand corner). Historical farm management data and data obtained through instrumentation deployed in the farm are used together with existing system knowledge to build the mathematical models describing the process. These data are also assimilated into the Digital Twin using data assimilation methods, thereby providing the link between the predictive models and the real asset. In sum, this provides the core of the Digital Twin implementation as implied in the left side of the figure.

The main direct uses of the Digital Twin are applications of the Digital Twin as a decision and policy making tool (upper left corner), or as a component in achieving the ability to assert optimal control of the process (top centre of the figure). In these cases, the Digital Twin needs to be in real-time or close to real-time contact with the physical asset to exploit the online data stream from this. Digital siblings (bottom of the figure), are not based on direct interaction with the asset, but rather represent purely hypothetical scenarios using the Digital Twin to explore the impact of situations or conditions on the asset without having to expose the asset to these. This enables risk free exploration of possible scenarios, which in an aquaculture setting could entail the ability to explore how expanding the farm with more cages, outbreaks of disease or challenging weather conditions may affect production without having to experience this in the real asset.

2.1.1. Instrumentation and data

The nature of the instrumentation (i.e., type of instrument, spatial and temporal distribution, sampling rates) needed to construct a Digital Twin will depend on the asset being studied, and needs to be designed such that it provides sufficient data to allow estimation of the system state with acceptable accuracy. The optimal setup for maximising the ability to capture the dynamics of the asset depends on both the asset and the purpose/aim of the Digital Twin. Conversely, a Digital Twin can also be used to optimise the instrumentation design by providing inputs on how many sensors/measurement points will be necessary to achieve good estimation of system states.

2.1.2. Models

Knowledge based models. Knowledge based models (KBM) are the most common tools for operationalising existing *a priori* knowledge, and there are several types of such models that could prove relevant for quantifying the dynamics in aquaculture production facilities. KBMs are built by synthesising knowledge on the system and its dynamics into mathematical equations that subsequently can be used to predict the responses of the system when subjected to a set of appropriate inputs. Due to their foundation in system knowledge, KBMs will often have a more clear cut line between measured data and the analysis of these.

Data driven models. In cases where the existing knowledge on system dynamics, components or elements is insufficient to develop KBMs, Data Driven Models (DDMs) may offer an attractive alternative. Developing DDMs requires datasets describing the set of known system inputs and the corresponding system outputs these will elicit. Methods from Artificial Intelligence (AI) and Machine Learning (ML) are then used to identify input/output transformations, enabling the prediction of system responses given a set of known inputs and initial/boundary conditions. Such models range from interpretable data driven models to pure black box input/output representations. While black box models are usually pure implementations of methods from AI and ML, interpretable models are usually also subjected to rules, limitations and boundaries defined for the asset at hand. Examples of such rules could be that the parameters of a neural network are found through evaluation against outputs that are required to adhere to periodic boundary conditions defined by the physics of a system or rules based on the physical properties of the system (for instance that the dissolved oxygen content of sea-water has an upper limit depending on factors such as temperature and local primary production).

2.1.3. Synthesising components into a digital twin

While instrumentation will handle the flow of data from the real asset to the Digital Twin in either real time or periodically, the use of KBMs and DDMs could be considered to serve a common purpose by adapting a Hybrid Modelling Approach (von Rueden et al., 2020). KBMs are then used to represent the part of the system dynamics known to science and that can be properly described by mathematical relations, while data driven elements are used to describe the remaining dynamics. This concept is central in Big data cybernetics, where the aim is to combine sophisticated mathematical models and Big data processing methods into a more robust and complete foundation for introducing feedback control of a system or asset of interest (Rasheed et al., 2019).

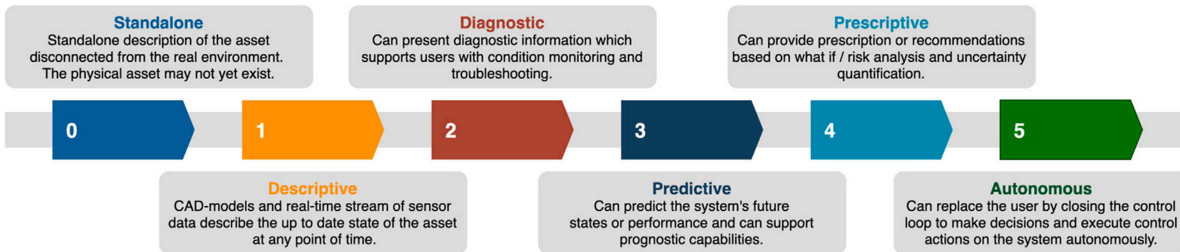

Fig. 3. Capability levels of Digital Twin.

2.2. Capability levels

The realism and completeness of the models and the degree of coverage achieved through instrumentation determine how close a Digital Twin resembles the asset it is intended to mimic. This also has a strong impact upon the capabilities of the Digital Twin, i.e., what it could potentially be used for. Based on the potential application of Digital Twin technology, it is possible to identify six distinct capability levels: 0-standalone, 1-descriptive, 2-diagnostic, 3-predictive, 4-prescriptive, and 5-autonomous (see Fig. 3).

Standalone digital twins. Standalone Digital Twins are categorised by being created solely based on existing knowledge on the system dynamics and hence do not have a link with the real asset/process in focus. As such, they may be considered purely model based precursors to Digital Twins of a system rather than proper Digital Twins (Jones et al., 2020; VanDerHorn and Mahadevan, 2021). This means that standalone Digital Twins can be constructed on the proposed specification of the asset before it is realised. One of their main values is that they can be used for preliminary cost–benefit analyses (profit margin, ecological/environmental impact assessment) of the asset before it is built.

Descriptive digital twin. Descriptive Digital twins utilise both real time or periodic data from instrumentation and models to provide a digital representation of the present state of the asset. They can therefore give a deeper insight into the inner workings of the farms at the required granularity. Descriptive Digital Twins can be used to visualise even those aspects of the asset which are not obvious to the naked eye. Their main value is that they keep all stakeholders (even those having no access to the physical farm) updated in real-time resulting in more informed decision making.

Diagnostic digital twin. If a descriptive Digital Twin is sufficiently accurate, it can be extended to become a diagnostic Digital Twin able to provide features such as fault detection and provide some degree of decision support. This requires that the Digital Twin is set up to explore, compute and assess the potential fault states and potential decision criteria.

Predictive digital twin. Although standalone, descriptive and diagnostic Digital Twins have their described benefits, neither of these have the ability to provide well founded insights into the future. This can only be achieved if the fidelity of the Digital Twin can be sufficiently increased by integrating data streams and models more tightly, and validating the outputs. The results of this process may be called a predictive Digital Twin, and requires that data streams are assimilated into the mathematical models using e.g., linear/nonlinear estimation methods. Predictive Digital Twins retain all the properties of the lower capability levels and can thus project the present as well as any past state into the future, a capability that is valuable for e.g., predictive maintenance or/and asset optimisation.

Prescriptive digital twin. The next step capability level is the prescriptive Digital Twin which also incorporates methods for making recommendations based on what if ? / risk assessment and uncertainty quantification based on the outputs of the Digital Twin.

These abilities are highly desirable for decision support systems.

Autonomous digital twin. The final step on the capability scale entails equipping the Digital Twin and the physical asset with bi-directional communication. The physical asset can then update its Digital Twin in real-time and in turn the Digital Twin can be set up to control the asset towards an optimal set point by closing the loop and applying model-based feedback control principles, in what can be referred to as an autonomous Digital Twin.

3. State of the art for digital twin technology in aquaculture

In this section, we will outline the state of the art within Digital Twin technology applied to aquaculture. We will first highlight a few scientific contributions that have aspired to at least partially fulfil the aims of Digital Twins in aquaculture, and then look deeper into the state-of-the-art within the main sub-components required to realise Digital twins, namely instrumentation, knowledge based modelling and data-driven models.

3.1. Digital twin concepts

Although Digital Twins have been identified as part of the solution to achieving precision farming, they have yet to become established tools in agriculture practices (Pylianidis et al., 2021). Applications in aquatic farming are even less mature than those in terrestrial agriculture. However, the industrial awareness of and interest in Digital Twins for aquaculture is increasing as seen in initiatives highlighting future possibilities (e.g., Ramos, 2021), or developments aimed at end products for the farming industry (e.g., Berthelsen, 2017; Russel, 2021; DNV GL, 2021). In research, there are also initiatives aimed at land-based production that are interesting for the discussion on Digital Twins for aquaculture, particularly those focused on intensive fish production through raceway systems (Lima et al., 2022) or recirculating aquaculture systems (RAS) (e.g., Zhabitskii et al., 2021). Others again have sought to develop Digital Twins for aquaponics/hydroponics that focused mainly on food production in the aquatic environment and less on intensive animal production (e.g., Ahmed et al., 2019; Sreedevi and Kumar, 2020; Ghandar et al., 2021).

There have also been some research initiatives on Digital Twins for cage based fish farming, most of which have focused on using the concept to monitor farm structural dynamics better. While some of these are mainly exploratory on the modelling side (e.g., Staalesen, 2019), others have sought to implement data assimilation methods for fusing model outputs with real-time sensor data (e.g., SINTEF Ocean, 2020; Su et al., 2023).

3.2. Instrumentation and observation

Instrumentation will always be a key component in a Digital Twin since it enables real-time tracking of the dynamics and states of the process. To capture the full system dynamics in aquaculture, it is thus necessary to apply instrumentation to monitor both the animal population and the physical structures and environment at the site.

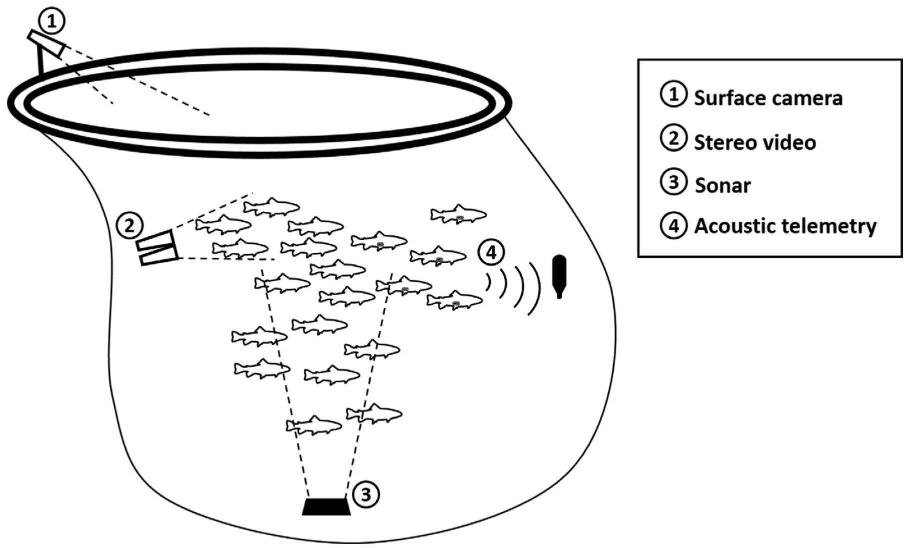

Fig. 4. Illustration of different methods for observing fish in sea-cages.
Source: Reproduced from Føre et al. (2018).

3.2.1. Animal monitoring

Fish in aquaculture production facilities may be monitored either at group or individual level using different types of technologies (Fig. 4). These two fundamentally different approaches to animal monitoring are largely complementary and can hence often be combined to acquire a holistic picture of animal states. However, for some applications, a purely individual or group focus may be sufficient.

Group level. The aquaculture industry has used technological solutions such as biomass frames to monitor size distributions in fish groups (e.g., Folkedal et al., 2012) for decades. While such solutions are likely to be important industrial tools also in the future, ongoing developments within enabling technologies are opening new avenues and possibilities for how the states of farmed fish groups can be objectively monitored. Machine vision coupled with subsurface cameras is the most common method for collecting group level data on fish in aquaculture fish farms, spanning a wide variety of specific applications (e.g., Zion, 2012; Saberioon et al., 2017). Some existing applications such as the assessment of fish swimming activity (e.g., Kolarevic et al., 2016; Georgopoulou et al., 2021), size (e.g., Hao et al., 2015; Voskakis et al., 2021), health condition (e.g., Jopling et al., 2021) and feeding activity (e.g., Måløy et al., 2019) may have particular importance for Digital Twin development as they provide data on some of the most crucial underlying biological processes at fish farms. Industry is also starting to pick up on the utility of machine vision in aquaculture (Stavelin et al., 2021), and several companies are now offering solutions that claim to enable quantifying such values, meaning that these methods are approaching industrial applicability. Some camera based systems also provide lice estimates as one of the outputs automatically derived from video footage.

The other main category of technologies for fish monitoring on group level are acoustic methods, that may again be divided into active and passive methods. Active methods are typically based on emitting acoustic pulses with known spectral characteristics, and then analysing the return pulses caused by reflections from objects within the observed volume. The complexity of the resulting data depends on the device type, ranging from basic 1D density distributions from echo sounders (e.g., Johansson et al., 2006), through 2D swimming speeds and fish sizes from splitbeam sonars (e.g., Arrhenius et al., 2000; Knudsen et al., 2004), to complete volumetric distributions and measurements using multibeam and high-frequency imaging sonars (e.g., Zhang et al., 2014; Cotter and Polagye, 2020, for wild fish).

Studies have also shown that it is possible to gain information on fish through passive acoustic monitoring (PAM), particularly during specific activities such as feeding (Kasumyan, 2008; Rountree et al., 2018; Rosten et al., 2023). Although passive monitoring is at a much earlier developmental stage than active methods, it has promise for future developments as it can be applied both omnidirectionally or aimed at specific areas using beam shaping methods (Chiariotti et al., 2019). While there are fewer industrial applications based on hydroacoustic methods than for cameras, there are companies delivering solutions for monitoring specific operations such as feeding or complete systems monitoring.

In addition to the technological approaches mentioned above, regular observations that are a part of the everyday farm management such as lice counts and mortality assessments can provide useful information on the state of the fish population. While these are usually acquired through manual inspection, their outcomes are typically inserted into a centralised control system and will as such be available for monitoring and/or control applications albeit not in real-time.

Individual level. Camera imaging and hydroacoustic methods can also provide instantaneous data on individual fish, e.g., by assessing individual swimming speed (Arrhenius et al., 2000; Georgopoulou et al., 2021) or individual fish sizes (Knudsen et al., 2004; Difford et al., 2020; Voskakis et al., 2021). Such information can provide insight into individual variations at that specific point in time, which can be useful information for understanding the dynamics observed at group level. However, these methods can generally not provide long-term data series for specific individuals, as they do not distinguish which individuals are currently being observed. Although individual identification can be achieved, at least for salmonids, by automatically recognising unique features such as dot patterns (Stien et al., 2017; Cisar et al., 2021), it is difficult to trace specific individuals over time using such methods as they target sub-volumes in the cage, usually from a static position.

Other monitoring methods, such as biosensors and telemetry, are designed specifically to produce individual histories of data (Thorstad et al., 2013). These methods require that the fish are first captured in the cage, and then anaesthetised. The fish are then equipped with electronic devices called tags either through surgical implantation or external attachment before being released back into the cage again. Suboptimal tag deployment may perturb a fish to the extent that they exhibit behavioural and physiological changes (Georgopoulou et al., 2022), potentially even leading to mortality (Macaulay et al., 2021), implying the need for proper interpretation of the dataset and expertise in fish handling and surgery (Jepsen et al., 2002). While these concerns render biosensors and telemetry a more complicated tool for industrial deployment, placing the equipment on or in the animal opens for the measurement of several parameters that are not possible to observe through optical or acoustic means (Endo and Wu, 2019; Brijs et al., 2021). Parameters that can be measured using commercially available tags range from behavioural traits such as activity (Føre et al., 2011; Kolarevic et al., 2016) and depth dynamics/positioning (Føre et al., 2017; Stockwell et al., 2021) to physiological parameters such as heart rate (Brijs et al., 2018; Hvas et al., 2020; Rosell Moll et al., 2021) and even gastrointestinal blood flows (Brijs et al., 2019). Moreover, the ongoing rapid developments in the fields of biosensor technology and microelectronics has led to the emergence of increasingly complex concepts able to measure hitherto unmeasurable parameters such as movement speed through mini-Doppler shifts (Hassan et al., 2020) and glucose and cholesterol (Endo and Wu, 2019). Coupled with the inherent ability to generate individual data histories, this expanding multitude of available data types implies that electronic tags can be a potent tool for obtaining information on individual sentinel fish in both research and potentially industrial applications (Føre et al., 2017).

3.2.2. Physical monitoring

The physical conditions of interest at a site can often be divided between those pertaining to the dynamics of the farm construction and those of the production environment.

Structural dynamics. Maintaining the structural integrity of the cages in a fish farm is the foremost measure in preventing escapes (Moe Føre and Thorvaldsen, 2021). Moreover deformations and movements in the various farm components may have an impact on the fish. It is thus important to monitor the movements and, if possible, deformations of the production units to get a full picture of the conditions affecting the fish. Some novel fish farming concepts are rigid structures (e.g., Ocean Farm 1, Salmar; Preline, Lerøy) whose dynamics can be estimated using data from sensors such as accelerometers, gyros and IMUs together with geometric considerations. However, most farms are still based on gravity type cages that are flexible and largely follow rather than resist water motions. Due to their flexibility, the full dynamics of such structures are notoriously difficult to monitor using available sensors. One of the few properties of gravity cages that can be reliably monitored with sensors are the gross loads acting on the structure. This has been done using load cells mounted between the cage and the mooring system, either in stationary farms (e.g., Fredriksson et al., 2003), or by towing or pushing cages at predetermined speeds using a ship (e.g., Gansel et al., 2018). The structural dynamics can also be monitored with a higher resolution through position sensors mounted strategically on the net structure, thereby obtaining the 3D position of these points in the net, which in turn are used to extrapolate the shape of the full net structure using mathematical models (e.g., Haugaløkken et al., 2018; Su et al., 2021). Structural monitoring can also include direct observations of net integrity, i.e., measurements aimed at detecting if there is damage to the net. This has previously mainly been done using solutions based on computer vision (e.g., Zacheilas et al., 2021; Madshaven et al., 2022) attached to mobile platforms that patrol the inner perimeter of the cage (e.g., Livanos et al., 2018; Amundsen et al., 2022).

Environment. Environmental monitoring is the most common type of monitoring in fish farming, partly due to governmental requirements to measure currents at a site before farm establishment, but also because fish farmers are seeing an increasing need to continuously monitor factors important for fish growth and welfare. This is also reflected within science, as studies aiming to explore fish responses toward cage operations and management (e.g., Oppedal et al., 2001; Føre et al., 2011; Erikson et al., 2016) often require environmental data as auxiliary sources of information. Some studies even aim specifically on studying variations in environmental factors (e.g., Burke et al., 2021), or how such variations impact fish behaviour (e.g., Johansson et al., 2006; Oppedal et al., 2011), growth (e.g., Cuenco et al., 1985; Solstorm et al., 2018) and welfare (e.g., Jónsdóttir et al., 2019). The most common instruments used for environmental monitoring in aquaculture are commercial off the shelf (COTS) sensors designed for long term monitoring of variables such as temperature (e.g., Johansson et al., 2006), oxygen (e.g., Solstorm et al., 2018) and salinity (e.g., Oppedal et al., 2019). Other environmental features such as wave spectra and water current require more complex instruments like Acoustic Doppler Current Profilers (ADCPs) or Acoustic Wave and Current Profilers (AWACs). Although such devices are usually more costly than conventional sensors, they are seeing increased use in research (e.g., Fredriksson et al., 2007; Michelsen et al., 2019), and are even included as permanent instruments in some of the more recently developed farming concepts for production further from shore. Environmental monitoring has recently been realised by using satellite data complemented with data from drones (Chatziantoniou et al., 2022) thereby providing data describing the conditions in a larger area than a cage or a farm, an approach that is of particular interest when organised aquaculture parks are operating or for monitoring HAB events (Nichols and Hogan, 2022). In this way, the monitoring of a larger area may provide insight on possible interactions between farms, particularly if coupled with hydrodynamic/oceanographic models.

3.3. Knowledge based models

Knowledge based models are likely to form the backbone of digital twins for aquaculture as they aggregate existing system knowledge. The idea of developing mathematical models for predicting the dynamics of farmed fish populations has existed for decades (Balchen, 1979). These early initiatives did not proceed beyond the theoretical level as their realisation requires a technological level that did not exist in the 70's. However, as the availability and capacity of computational resources and other technological tools has increased in time, so have the possibilities and opportunities within mathematical modelling and simulation of increasingly complex systems. Although this has resulted in a large body of predictive models seeking to represent various sides of the dynamics of fish farms and the processes therein, aquaculture production facilities are inherently interdisciplinary systems and need to be treated as such. Successfully developing a Digital Twin that captures the full system dynamics in a fish farm will therefore require a combination of models able to predict the biological (e.g., behaviour, growth, welfare), physical (e.g., structural, hydrodynamic) and environmental dynamics at the site. We will in the following outline the current status on knowledge based modelling in fish farming, where theory and knowledge on fish and fish farming systems is synthesised into predictive models, first covering models aimed at the biological aspects (i.e., fish behaviour and growth) and then those replicating physical/environmental dynamics. Fig. 5 describes four concrete examples of models within these categories aimed at aquaculture applications.

3.3.1. Biological models

Behavioural models. Unlike simpler organisms such as zooplankton (e.g., Alver et al., 2006) or fish larvae (Lika and Papandroulakis, 2005), adult fish have explicit behaviours that are important components in how they cope and interact with the culture conditions, assimilate nutrition and develop in the production unit. Models portraying fish behaviour will therefore be crucial elements in the development of a Digital Twins of fish farming operations. Although the potential importance of behavioural modelling in controlling fish production was first implied in the 70's (e.g., Balchen, 1979, 2000), there have been few attempts at creating generic models for portraying the behavioural dynamics in farmed fish populations. This may be due to the difficulty of finding sufficient high quality data to develop and verify reliable and

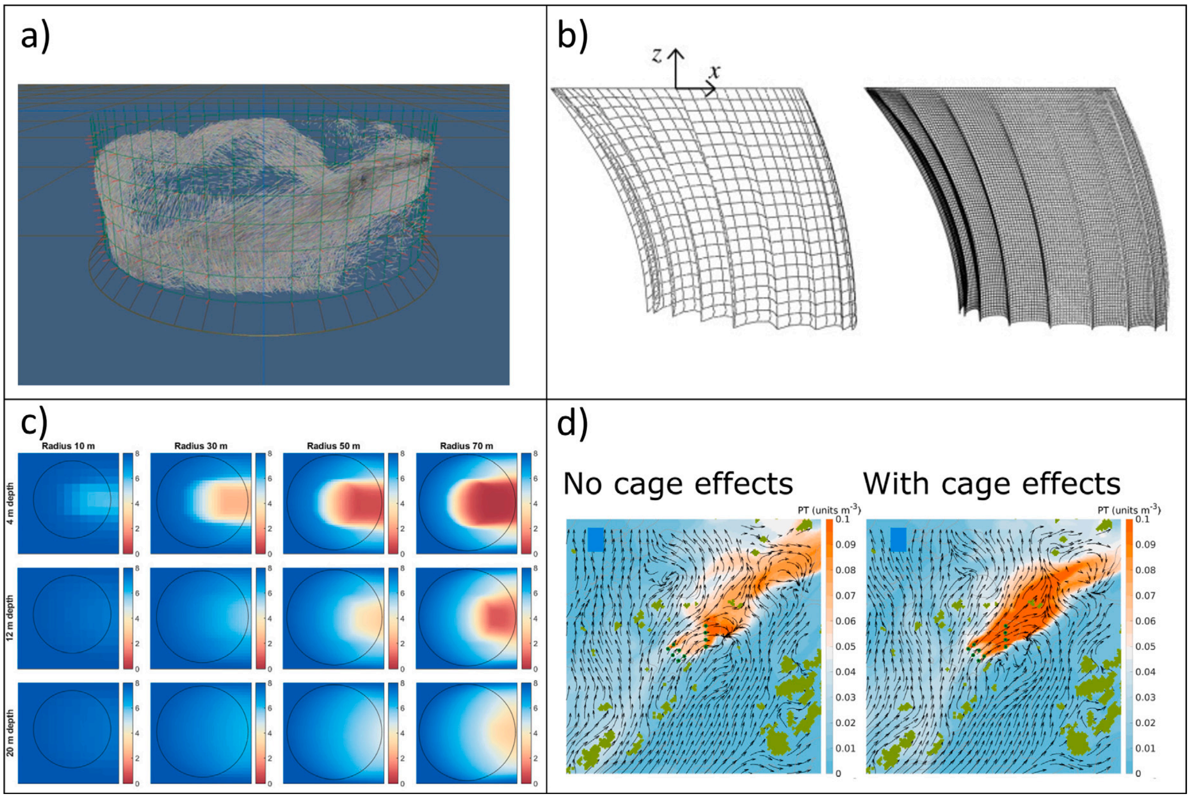

Fig. 5. Examples of Knowledge based models aimed at aquaculture processes. (a) individual based fish behaviour model simulating movements in sea-cage (simulation based on the model presented by Føre et al., 2009); (b) Finite Element Model representing net cage deformations (reproduced with permission from Moe et al., 2010); (c) advection–diffusion type model used to simulate oxygen flow and depletion in sea-cages of various sizes (reproduced from Alver et al., 2023); (d) (c) oceanographic model used to simulate distribution f particulate matter from fish farms in larger spatial scales (reproduced from Broch et al., 2020).

realistic predictive models. Attempts have been made at synthesising knowledge based on echo sounder observations in sea-cages into an individual based model of salmon behaviour (Fig. 5a, Føre et al., 2009). These models provide insight into the dynamics of vertical distributions and group migration patterns in salmon, but not other elements such as how realistic the horizontal distribution patterns or individual response patterns are. Further development of such models to also cover these aspects will probably require the use and assimilation of data from other sources, such as biosensors/telemetry and cameras, that have both been in rapid development in later years.

Growth models. Fish growth is easier to objectively quantify than behaviour, and can be assessed either through manual sampling (e.g., comparing individual fish weight at different times), or by using technological tools specifically designed to estimate fish size. Moreover, since fish growth is intrinsically linked with the economic profit of a farming operation, the industry has practised growth tracking throughout the history of aquaculture. This has resulted in a data and knowledge base available for the development of fish growth models that is considerably more concise and comprehensive than that for developing behaviour models. From this base, it has been proven possible to develop models describing how farmed fish growth is affected by feeding methods (e.g., Cho and Bureau, 1998) and environmental features such as temperature and oxygen (e.g., Cuenco et al., 1985; Björnsson et al., 2007; Stavrakidis-Zachou et al., 2019; Stavrakidis-Zachou et al., 2021). The approaches applied to model growth in farmed fish range from early attempts on basic curve fitting between fish weight and age (e.g., Chen et al., 1992), to more knowledge based approaches seeking to replicate the internal energetics of the organism (e.g., Kooijman, 2000; Nisbet et al., 2012; Nobre et al., 2019).

3.3.2. Physical and environmental models

Fluid–structure interaction. Although basic physical relationships and equations can be used to predict the hydrodynamic forces acting on individual cage components, modelling a full cage system comprised by interconnected components requires data for development and subsequent validation. Sea-cages have therefore received much attention from engineers and researchers seeking to map their hydrodynamic interactions with the environment (as reviewed by Klebert et al., 2013) Although some studies have also been conducted in full-scale fish farms (e.g., Fredriksson et al., 2003; Lader et al., 2008), most of this data and knowledge has been obtained through scaled down studies in laboratories where it is possible to monitor and control both conditions and structural responses with high accuracy (Moe-Føre et al., 2016; Dong et al., 2019). When scaled up accordingly, it is possible to use the outcomes from such studies to describe the expected system dynamics, and hence the responses and tolerance of the structure towards environmental factors. This has led to a vast body of knowledge on the dynamic interaction of flexible sea-cages that has in turn been used to derive different models describing the loads and deformations exhibited by cages and their sub-systems when subjected to environmental forces like currents and waves (Fig. 5b, e.g., Tsukrov et al., 2003; Moe et al., 2010; Dong et al., 2010). Other studies have also looked into how cage structures in turn affect the ambient and cage-internal environment (e.g., Klebert and Su, 2020), either by full Computational Fluid Dynamics (CFD) analyses (e.g., Winthereig-Rasmussen et al., 2016), or by "line-of-sight"-based approaches to predict shadow effects (e.g., Løland, 1993; Endresen et al., 2013).

Cage environment models. Models that seek to describe the dynamics behind particle movement and distribution in volumes have also several applications in modelling the dynamics in aquaculture production units. These models can either be based on generic modelling paradigms like CFD or be custom made frameworks designed to model specific phenomena, and have previously been used to simulate the feed distribution in fish farms in 2D (Alver et al., 2004) and 3D (Alver et al., 2016), and particle removal from production units (e.g., Klebert et al., 2018). Although it is difficult to assess the accuracy of such models in full-scale aquaculture situations, a recent study used an advection–diffusion based model to simulate oxygen distribution in sea-cages, and validated it using measurement data from a large rigid sea-cage (Fig. 5c, Alver et al., 2022, 2023).

Ambient environment models. When modelling the cage environment, it is also necessary to identify methods for representing the dynamics in the ambient environment both close to or far from the fish farm as these can provide the boundary conditions for the models simulating the in-cage dynamics. There are several different oceanographic models (e.g., Slagstad and McClimans, 2005; Shchepetkin and McWilliams, 2005; Urke et al., 2021) that fit the purpose of estimating the physical and chemical conditions in regions of various sizes and resolutions. Such models have been used for purposes ranging from forecasting oceanographic conditions (e.g., Slagstad et al., 2011), through data assimilation (e.g., Moore et al., 2011), to multi-scale modelling in conjunction with CFD (Fig. 5d, e.g., Broch et al., 2020). While oceanographic models can provide inputs on currents, nutrient flows and other physical/chemical properties, a Digital Twin will also need some way of assessing the local effects of waves, particularly when considering operations in more exposed areas (Bjelland et al., 2015). This role could be fulfilled by models designed to predict coastal wave generation (e.g., Sukhinov et al., 2013), or by combining models relating wind and waves (e.g., Chalikov, 1978) with farm wind exposure analyses (e.g., Lader et al., 2017).

3.4. Data driven models

More recently, data-driven modelling has become increasingly popular due to the abundance of big data, easy-to-use machine learning libraries, cheap computational infrastructure, and readily available training resources. These models are built on the assumption that data represents both known and unknown physics. With enough data, data-driven models can learn the underlying physics on their own, resulting in models that achieve super human-level performance in tasks previously deemed impossible for computers.

Any data-driven model can be put in one of the six categories. These models in the context of aquaculture is explained below:

3.4.1. Supervised linear models

These models are trained with labelled data, where the target variable is known. Linear regression and logistic regression are examples of this type of model. They are simple and efficient and can be used for tasks such as prediction, classification, and feature selection. In a comparatively early study, Palomares and Pauly (1989) developed a regression model able to predict food consumption in marine fish, while a more recent study by Sara et al. (2009) demonstrated the utility of such models in describing and predicting growth and feed intake in marine prawns. While these studies were not aimed at cultured animals, they illustrate the potential usefulness of such models also in aquaculture.

3.4.2. Unsupervised linear models

These models are trained with unlabelled data, where the target variable is unknown. Principal component analysis (PCA) and linear discriminant analysis (LDA) are examples of this type of model, and can be used for tasks such as dimensionality reduction, feature extraction, and clustering. There have been previous studies using such methods towards aquaculture applications, exemplified by Simonnet-Laprade et al. (2021) who demonstrated strategies for the characterisation of chemical contaminant mixtures in the contest of fish contaminant using PCA and LDA.

3.4.3. Supervised non-linear models

Models belonging to this class are trained with labelled data, are more flexible than linear models, and include well-known approaches such as decision trees, support vector machines (SVMs), and random forests. Such models can capture complex relationships between the features and the target variable, and have often been used in combination with cameras and other machine vision components (Saberioon et al., 2017). In a recent study, Palaiokostas (2021) assessed SVM, and various tree based methods in terms of their efficiency to predict disease resistance in both simulated and real-life aquaculture datasets, also considering the computational cost associated with the training of different models.

3.4.4. Unsupervised non-linear models

These models are trained with unlabelled data, are more flexible than unsupervised linear models and include notable model types such as Self-organising maps (SOMs) and K-Nearest Neighbour. Unsupervised non-linear models can be used for tasks such as clustering, anomaly detection, and data compression. Example applications from aquaculture include Russo et al. (2010) who utilised SOM to study of skeletal anomalies and meristic counts in gilthead seabream, and Iswari et al. (2017) who demonstrated a fish freshness classification method based on applying k-Nearest Neighbour to fish images.

3.4.5. Supervised deep learning

Supervised Deep learning models are trained with labelled data and complex architectures. Convolutional neural networks (CNNs) for image recognition, recurrent neural networks (RNNs) for natural language processing, and fully connected deep neural networks for regression and classification tasks are prominent examples of models belonging to this class. Deep learning models can achieve state-of-the-art performance in many tasks and are highly flexible. Some recent examples belonging to this category include the use of neural networks to predict feed intake in rainbow trout based on water temperature, oxygen, average weight and number of fish (Chen et al., 2020), and the use of Q-learning to track fish growth trajectories (Chahid et al., 2022). Moreover, Måløy et al. (2019) and Måløy (2020) used deep learning methods to derive behavioural parameters from video footage and echo sounder data collected from farmed salmon.

3.4.6. Unsupervised deep learning

These models are trained with unlabelled data and complex architectures. Generative adversarial networks (GANs) for image synthesis and unsupervised feature learning and autoencoders for data compression and anomaly detection are examples of this type of model. Unsupervised deep learning models can be used for tasks such as unsupervised feature learning, anomaly detection, and generative modelling.

4. Concept studies

The preceding literature review shows that many of the components required to design a Digital Twin of an aquaculture fish farm exist. However, to achieve this goal, we need to combine these components into a complete solution that maintains the properties we require from a proper Digital Twin. In this section, we will illustrate this by outlining three concrete cases that are founded in published experimental studies. For each case, we will first describe elements within the three main component classes (i.e., knowledge based models, real-time data collection systems and data driven models) needed to build the Digital Twin for that case. We will then suggest how these elements can be integrated into a common system, before finally suggesting potential industrial applications for the resulting Digital Twin.

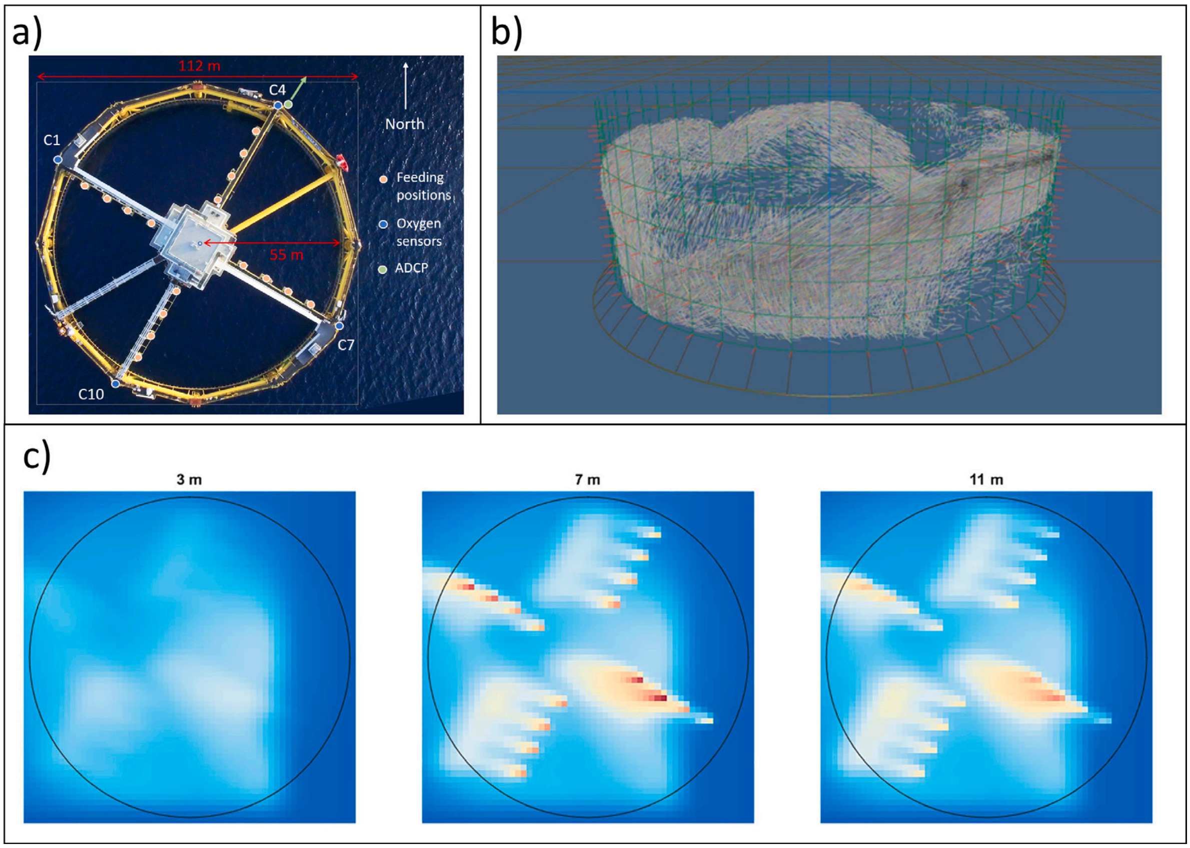

Fig. 6. Components that could be components in a Digital Twin aimed at concept 1. (a) instrumentation package to collect data on e.g., oxygen and current conditions in the cage volume (Reproduced with permission from Alver et al., 2022); (b) mathematical individual based model of fish behaviour (simulation based on Føre et al., 2009); (c) advection–diffusion models for simulating the distribution and depletion of oxygen through the cage volume (Reproduced with permission from Alver et al., 2022).

4.1. Concept 1: Oxygen conditions in sea-cages

4.1.1. Background

Fish farmers have a strong motivation to avoid hypoxia events (e.g., Remen et al., 2013) where dissolved oxygen levels drop to a level that can cause stress and other welfare-compromising effects (Remen et al., 2012), potentially even increasing the likelihood of disease outbreaks and acute mortality (e.g., Abdel-Tawwab et al., 2019). Whereas terrestrial farming operations can ensure sufficient oxygen through active ventilation, the higher density of water and size of the volumetric flow through a cage, which depends on a variable current speed, renders this more challenging in fish farming. Moreover, the nominal oxygen concentration in water (less than 1%) is much lower than in air (about 20%), and is also very sensitive to water temperature. These effects imply that it is important to monitor dissolved oxygen levels in fish farming, both to provide decision support for the farmer, and to serve as a foundation for future solutions for improving the oxygen conditions in sea-cages. A Digital Twin reflecting the distribution of dissolved oxygen in sea-cages is a potential first step in achieving this level of control. In a recent study, a mathematical model of how dissolved oxygen propagates through the production volume of a large-scale rigid cage structure (Ocean Farm 1, Fig. 6) was presented and validated (Alver et al., 2022), and has been further used to analyse how cage size affects oxygen levels in sea cages (Alver et al., 2023). This model can form the basis for the Digital Twin concept outlined in the following.

4.1.2. Knowledge based models

Alver et al. (2022) (Fig. 6a, c) compared their model predictions with data series collected for low, moderate and high current speeds by oxygen sensors placed at 12 m depths at four positions along the outer perimeter of the cage. Although this validation proved the model able to predict most of the dynamics in dissolved oxygen levels within the cage, the study also identified some potential future expansions that could improve its performance in generic cases, several of which were associated with the oxygen consumption of the fish. One key element was that the distribution of the fish within the volume was represented by qualitative assumptions on how the fish distribute in response to feeding. A more advanced behavioural model for reflecting the movements and distribution of fish could contribute to increasing the realism in this aspect. This could be done by integrating the oxygen model with existing models of fish behaviour in sea-cages (Fig. 6b, e.g, Føre et al., 2009, 2016), if these models were first calibrated to the structural properties and environment of the asset targeted by the Digital Twin.

4.1.3. Real-time data collection

The dataset used by Alver et al. (2022) featured data collected using hard-wired oxygen and temperature probes and current profilers placed outside the cage (Fig. 6 a), and feed delivery signals from the farm management system. Although this provided a sufficiently good picture of the oxygen dynamics in the cage, a higher resolution and hence precision could be obtained by also collecting oxygen data and current data from the volume inside the cage. This could enable both a more thorough validation of the model, and provide a better foundation for assimilating current and oxygen data with the model. There were also 12 scientific echo sounders (EK80, Kongsberg Maritime) deployed at the site during the trials that can provide echograms describing the distribution of the fish, and split-beam functionality that can be used to assess individual fish size (Knudsen et al., 2004) and swimming speeds (Arrhenius et al., 2000). While these data were not employed by Alver et al. (2022) as their analyses would be a considerable research task in itself, a future Digital Twin of this system could benefit from also exploiting these data types to better describe fish distribution and sizes.

4.1.4. Data-driven models

While the inter-calibration between the oxygen probes used by Alver et al. (2022) could be categorised as a form of machine learning, it is possible that data-driven models could serve a bigger purpose by portraying some of the elements that are less clearly defined in the knowledge based models. Considering the large amounts of data produced by hydroacoustic systems, it would be particularly relevant to look at such methods for analysing fish distributions and responses toward the prevailing conditions in the cage. Previous work on this area has resulted in methods able to classify different types of fish behaviour and even detect disease outbreaks by applying deep learning methods to hydroacoustic data collected from sea-cages (Måløy, 2020). Similar methods could also be used as a means to develop data-driven models able to predict fish distribution based on a set of input parameters (e.g., temperature, feeding, light).

4.1.5. Module integration

The first integration step required to develop the Digital Twin for this case would be to facilitate a real-time link between the sensors and the mathematical model. For the instruments already attached to the cage structure (i.e., oxygen probes, temperature sensors, echo sounders) the main technical task would be to provide a communication link for forwarding the data streams from these to the computer running the model. Successful integration would also require the development of an interface for assimilating the data into the model. Temperature and current measurements, as well as oxygen measurements outside of the farm representing ambient conditions, could be used in real-time to provide appropriate input values to the oxygen model. Data from oxygen sensors within the model domain could be used directly by comparison to predicted values at matching positions, using an Ensemble Kalman Filter (Evensen et al., 2009) or other approaches to compute model corrections.

Echo sounder data would require more extensive processing and translation before being assimilated into the model. This would entail both the synthesis of data from all 12 echo sounders into a common dataset, and deriving fish distribution estimates from this. The resulting datastream could then be both assimilated into the knowledge based behavioural model and be used to train the data driven model of fish distribution. These models could then be set up in the cascade structure proposed in the Big data cybernetics approach (Rasheed et al., 2020). This would effectively exploit real-time data, knowledge based modelling and data driven models to acquire a better estimate of dissolved oxygen distribution in sea-cages. Finally, developing a human machine interface to present and visualise the twinned cage oxygen conditions to the user would finalise the Digital Twin for their application.

4.1.6. Industrial applications

The most apparent benefit of achieving a fully functional Digital Twin of the oxygen distribution in sea-cages is that it will provide farmers with a more complete picture of the oxygen situation in a sea-cage than possible through either measurements or model simulations alone. This can in turn be used as a means for decision support to ensure that cage management practices or operations do not lead to the fish being too exposed to hypoxic conditions. One example where this could be applied is feeding, as feeding activity is a key factor behind both the consumption of and requirement for oxygen in fish (Forsberg, 1997). The farm used in the study by Alver et al. (2022) is equipped with 16 individual feeding points, and in cases where oxygen levels are low, it could be beneficial to suspend feeding or only deliver feed through the feeding points that are upstream from the midpoint of the cage to prevent feeding under sub-optimal oxygen conditions. Digital Twins could also have a role in counteracting hypoxic situations after they have arisen. Active oxygenation of an entire full-scale sea-cage is unrealistic, as this would require oxygenation equipment of a scale that is practically and economically unfeasible to use in a production situation. The placement of the oxygenation diffusors used by the industry must therefore be chosen with care. A Digital Twin could predict the most strategic diffusor placement, and monitor the impact of the operation so that the placement can be optimised. Such Digital Twins would perhaps be even more relevant when considering closed containment systems, a type of systems that comprises both land-based recirculation aquaculture systems (RAS) and closed/semi-closed marine systems. Since these are systems that are designed to operate with little or no exchange of water with the surroundings, it is even more crucial to maintain close control over the developments in oxygen concentration and distribution inside the production system to avoid unfavourable conditions.

4.2. Concept 2: fish growth in sea-cages

4.2.1. Background

The biomass is the most important parameter for fish farmers, as it both conveys how they best can manage farm operations such as feeding, and enables them to assess the future crop value. Estimating the size distribution of the fish is also crucial for value assessment, as the fish are sold not as a bulk but according to size classes. The precision of such applications could be further improved if one was able to also quantify the number of individual fish in the cage. Previous studies have sought to explore how the current state-of-the-art can be used to improve feeding efficiency in salmon farming. However, a Digital Twin merging relevant mathematical models and real-time data from available sensors and instruments could provide the means to achieving a better overview of these parameters.

4.2.2. Knowledge based models

Føre et al. (2016) (Fig. 7d) sought to simulate the growth process in full-scale sea-cages by combining a behavioural model (Føre et al., 2009) with an energetic model (Kooijman, 2000) and a feed distribution model (Fig. 7c, Alver et al., 2016). While the model was originally developed for simulating Atlantic salmon, its modular design allowed for easy adaptation to other species by adapting the behavioural and/or energetic modules to other species (e.g., Stavrakidis-Zachou et al., 2019). The model was run using the feed delivery regime and environmental data series measured at the site during a long term growth experiment as input. Its outputs in the form of growth data were then compared with growth data collected through periodic manual samples and automated measurements using a biomass frame. The model proved able to track the growth of the fish relatively closely in the first half of the experiment, implying that it captured most of the growth dynamics for salmon under normal conditions. However, midway through the experiment, the fish contracted Pancreas Disease (PD), the effect of which was clearly seen as a reduction in growth. The model was not able to predict the growth accurately in this period, and since it operated with the same feeding rates and environmental conditions as at the experimental site, this deviation probably arose because the model had no means of representing the effects of disease. While it is unclear if this growth deficit was due to reduced feed intake or a direct physiological response in the fish, expanding the model with the ability to simulate how pathogens or parasites affect fish growth would add to the realism of the model and hence an eventual digital twin based upon it. These models cover most of the important components to represent fish growth and typically rely on a limited number of forcing variables such as temperature and feeding regime. Their accuracy could be improved by including more detailed models of the environment such as dissolved oxygen (Alver et al., 2022), pH, salinity, turbidity and water currents, and how the fish respond to these.

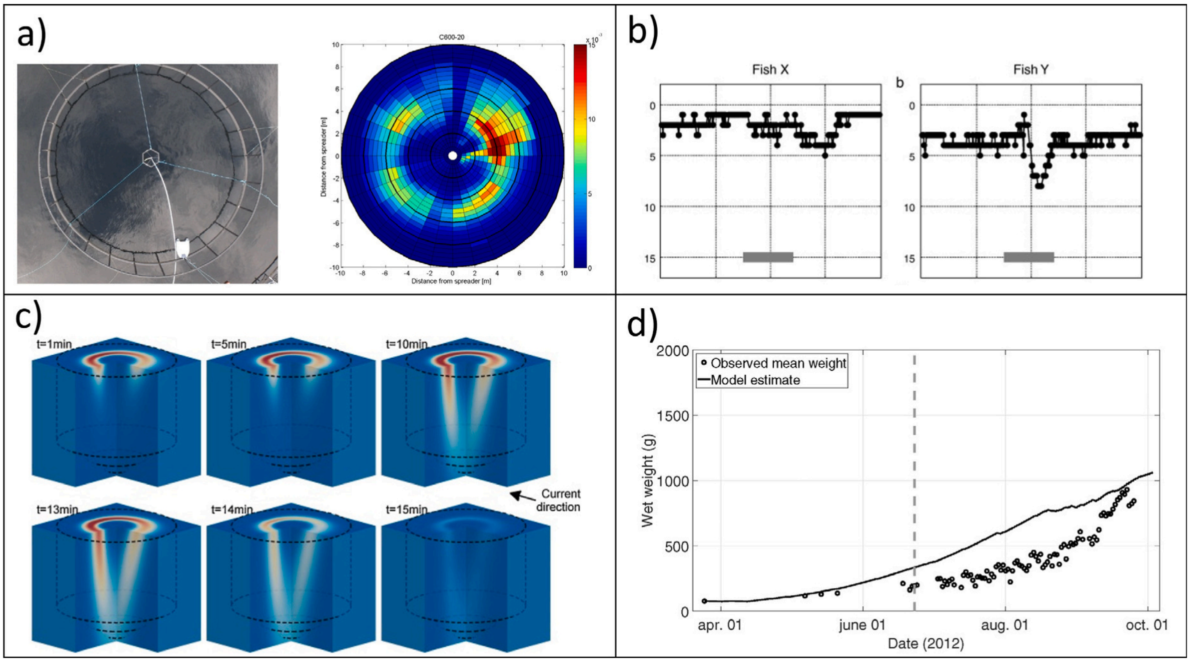

Fig. 7. Components that could be components in a Digital Twin aimed at concept 2. (a) computer vision methods to automatically estimate surface distribution of pellets (right) by analysing aerial photos of the cage surface (left) (Reproduced with permission from Lien et al., 2019); (b) telemetry methods to measure individual fish depth movements before, during and after feeding period (marked by grey bars) (Reproduced with permission from Føre et al., 2011); (c) advection–diffusion models for simulating the distribution of feed pellets in the cage volume (Reproduced with permission from Alver et al., 2016); (d) growth models able to estimate and predict individual fish growth (Reproduced with permission from Føre et al., 2016).

4.2.3. Real-time data collection

The automated data sources used in the original study (i.e., feeding signals, environmental sensors, biomass frames) would probably be useful when designing the Digital Twin. Additional insight could be obtained by using behavioural data from devices such as cameras (e.g., An et al., 2021), echo sounders (e.g., Bjordal et al., 2020) or telemetry (Fig. 7b, e.g., Føre et al., 2011) to tune or correct the feeding behaviour of the fish. From a holistic point of view, echo sounders could also have a potential in providing data describing the total biomass in the system and how this biomass is spatially distributed. This would require that the device could observe the entire cage volume, and more refined technologies/processing methods than extant today, but could become a reality in the future due to ongoing developments within both hydroacoustic technologies and use of these in cages. Precision could be further improved by expanding these setups, by e.g., measuring environmental data with a higher spatial resolution or trying to better quantify feed distribution (Fig. 7a, e.g., Lien et al., 2019) and loss (e.g., Skøien et al., 2014). The data on fish sizes could probably likewise be improved by increased resolution, e.g., by placing several biomass frames/sensors at different depths or using stereoscopic camera systems (Voskakis et al., 2021). This could potentially compensate for eventual measurement errors due to size-dependent vertical stratification in the fish distribution, as has been observed in salmon cages (Folkedal et al., 2012). Moreover, since elevated and/or prolonged swimming activity may have impacts on fish growth (Waldrop et al., 2018; Hvas et al., 2021), data describing the water movements induced by currents and waves would be useful inputs for better predicting fish growth in sea-cages. Such data would be particularly interesting for operations in more exposed and energetic environments (Bjelland et al., 2015; Jónsdóttir et al., 2019), and can be collected by a wide variety of commercially available devices (e.g., Acoustic Doppler Current Profilers, Acoustic Wave And Current Profilers).

4.2.4. Data-driven models

Fish farming companies and fish feed producers routinely run feeding trials and experiments to e.g., explore new feed types, resulting in datasets describing both the weight development and the driving factors behind this process over time. Such datasets are usually restricted from public access as they may feature information that can divulge the effects of e.g., feed composition or feed delivery methods on growth and hence profitability that are proprietary to the owner of the data. However, if these data were made sufficiently anonymous and cleaned of eventual details that could reveal company secrets, and then were made available for science, they could be a foundation for developing accurate data-driven models of fish growth that could be used as a component in a Digital Twin aimed at fish growth (Aunsmo et al., 2014). Data-driven models could also serve a purpose in providing a means for modelling features not captured by the knowledge based growth models such as disease effects. One of the main shortcomings of the model used in the original study was its inability to represent the growth effects induced by the onset of disease. Using the dataset that describes the difference between the expected (i.e., model predictions) and actual (i.e., growth measurements) growth in that trial, it could be possible to set up and train a data driven model able to predict the effects of PD on fish growth. If similarly detailed growth data could also be collected for cases where fish are subject to other disease and parasite outbreaks, repeating this exercise could result in a collection of data driven models able to predict the effects of such events on fish growth. Such models would also be useful and interesting results in themselves.

4.2.5. Module integration

Since the instruments required to achieve a minimum of data coverage for this case are mostly commercial products that often feature interfaces for external communication, their integration with models would mainly entail a setup of reliable communication channels for transferring their data to databases available to the simulation models and assimilation schemes. Data driven models of disease effects could

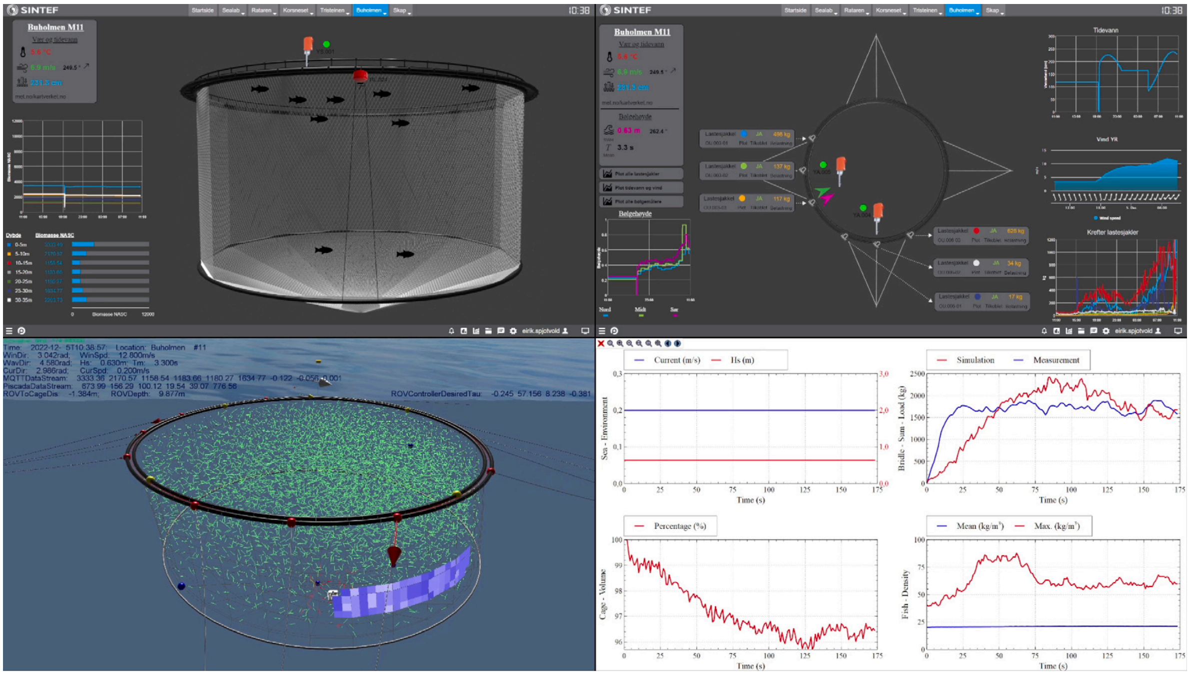

Fig. 8. Case 3: An example of an advanced starting point for a full Digital Twin for in-cage robotics and vehicle operations (SINTEF, 2023). This example showcases various components of a Digital Twin application, including a description of the setup of sensors for monitoring the fish (upper left) and the cage structure and physical conditions (upper right), an online digital rendition of the situation in the cage (lower left), and data histories from instruments over time (lower right).

potentially be implemented as a module in the knowledge based growth model to account for such effects. In its most basic form, this could be done by simply scaling the growth rate of the fish directly in accordance with the output from the model. Although this approach could be sufficient to compensate for the shortcomings of the mathematical model on this area, it would not reveal the specific reason for the growth reduction during disease outbreaks. This could potentially be explored further by trying to identify what specific mechanisms (e.g., reduced appetite, increased energy expenditure) in the growth process are actually causing the growth deficit seen during disease. Ideally, this endeavour would entail conducting specific laboratory and field experiments on pathogen–host interactions and disease effects on metabolism to unravel the biochemical pathways that explain the observed growth deficit. In turn, this could contribute to the integration of these mechanisms into the growth models by the addition of disease-related knowledge based modules or the adjustment of appropriate model parameters. Considering the theoretical and practical challenges, such as data availability, in developing truly knowledge based models for diseases, one possible indirect way to include such effects could be to run simulations with the knowledge based model where the growth reduction is introduced through different model components. For instance, such effects could be introduced as reduced feed intake or direct reduction in metabolism due to increased energetic maintenance needs related to the immune response of the fish rather than as a direct factor on growth rate. Although this is a manual approach that would not transform the data driven model entirely into a knowledge based representation, it could be a step towards better understanding the growth dynamics in fish. Devising a human–machine interface that presents the estimated growth data in a good manner to the user would finalise this Digital Twin. This interface could possibly also contain options for visualising the growth together with chosen features of the production environment such that the user can highlight relationships between these and the growth.

4.2.6. Industrial applications

A Digital Twin describing fish growth in sea-cages could foremost provide the farmer with a better overview of the properties of the biomass and its daily development, which is important information when assessing feeding efficiency and the effects of environmental conditions, as well as planning of the future marketing of the fish. This information can also be crucial from a decision support viewpoint, as knowing the total biomass and size distribution in a cage can be important both in determining a suitable feeding plan and for critical operations such as crowding. Moreover, in predicting the expected growth rate and being able to compare this with real-time data, the Digital Twin could also provide a method for early detection and warning of undetected disease outbreaks and other unwanted effects. If the model is also equipped with models that account for the effects of different diseases/parasites, it could even potentially suggest the specific cause behind the growth reduction. Finally, if the Digital Twin is properly validated against real situations, it could also be used to close the loop of cage-based fish production. By providing feedback control signals on growth and spatial feed distribution, one could actively control farm management operations such as feeding. This would be a step towards enabling fish farms to operate autonomously without human intervention, a feature that could be particularly beneficial for farming operations at more exposed sites (Bjelland et al., 2015). Although this may lie some years further into the future than the other potential applications, a similar approach has previously been used for autonomous control of rotifer cultures (Alver et al., 2010).

4.3. Concept 3: in-cage robotics and vehicle operations

4.3.1. Background

More extensive use of advanced robotics in industrial production is an important step in achieving the automation aims proposed in the Industry 4.0 paradigm (Vaidya et al., 2018). This notion has also been transferred to the aquaculture industry, where there is an increasing interest in using robotics to replace manual labour, particularly for Dull, Dirty, Dangerous, Distant and Dear (5 D's) jobs. Such jobs are even more challenging at more exposed or offshore locations, where there is also a higher demand for robotics and automation as human presence is more difficult due to the harsher environmental conditions (Bjelland et al., 2015). Digital Twins seeking to mimic robotics operations in flexible sea-cages can prove to be key components in developing and testing operations with remote piloted/unmanned vehicles and/or robotic manipulators (e.g., net inspections with an ROV, as shown in Fig. 8). The use of robotic platforms for autonomous and continuous high-quality data collection in sea-cages has been explored by Rundtop and Frank (2016) and Kelasidi et al. (2022) through full scale trials studying in-cage navigation with an ROV using different sensor solutions, and by Livanos et al. (2018) in a simpler approach using off-the-shelf equipment while developing appropriate algorithms. This type of research has been stimulated by currently increasing industrial trends on adapting robotic solutions to aquaculture, and investigating their autonomous capabilities in relevant applications in sea-based and land-based fish farms. The relevance of this research and potential industrial applications of robotic system were recently reviewed by Kelasidi and Svendsen (2022). Expanding this study with knowledge based and data driven models would introduce predictive powers and utilise existing knowledge, representing a solid foundation for developing a Digital Twin for this case.

4.3.2. Knowledge based models

In addition to describing the vehicle dynamics (e.g., Ohrem et al., 2021), a mathematical model base for a Digital Twin for this purpose would need to define several aspects of the spatial dynamics facing a vehicle or robot inside a cage. This includes the cage structure (e.g., Moe et al., 2010; Kristiansen and Faltinsen, 2015) and its interactions with the environment (e.g., Klebert and Su, 2020), as well as the movements of the fish (e.g., Føre et al., 2009). Su et al. (2019) synthesised all these elements (i.e., marine environment, fish, cage and vehicle operations) by using a module based modelling framework (Reite et al., 2014). Although the resulting model could be used to simulate the spatial dynamics in a sea-cage, there are still limitations related to its ability to reflect the full system dynamics. While some of these are possible to derive from existing knowledge, other aspects are less well-known by science and hence difficult to model. One such aspect is how fish respond to the presence and movements of a vehicle or robot, which is a key question to answer before one can fully exchange human intervention with robotics at fish farms (Kruusmaa et al., 2020).

4.3.3. Real-time data collection

The most essential real-time element needed for this application is the ability to detect the position and movement of the vehicle, and its proximity to other objects in the cage. Ultra Short Baseline (USBL) and Doppler Velocity Log (DVL) devices were tested for this purpose by Rundtop and Frank (2016) and Amundsen et al. (2022), and are suitable candidates for the future development of a Digital Twin. Such systems could also be complemented by pressure sensors, providing a better estimate of depth, and current (ADCP) or wave profilers (AWAC) to assess hydrodynamics and hydraulics at the site. Acoustic positioning systems could also be used to measure the positions and velocities of structural components at the farm, and could in combination with mathematical models, even estimate the deformations of flexible components like net structures (Su et al., 2021). Recent studies have also shown that it is possible to utilise autonomous underwater vehicles (Kelasidi et al., 2022) to collect data for in-cage navigation through camera based solutions (Schellewald et al., 2021). Cameras can also be used to automatically collect data on biofouling levels (Gansel et al., 2017), and fish behaviour/movements (e.g., Saberioon et al., 2017; Måløy et al., 2019), which would be useful for assessing the structural motions/deformations and fish distributions, respectively. Moreover, acoustic devices such as echo sounders or sonars would be useful sources of information on fish distribution and movement, and could be fitted onto the vehicles.

4.3.4. Data-driven models

Assuming that vehicle position and movement is known, and that the vehicle has some method of quantifying the movements of nearby fish, it could be possible to design a data driven model able to predict fish responses based on vehicle motions. This could eventually be complemented with Guidance Navigation and Control (GNC) data (Fossen, 1999) from the vehicle to also analyse if accelerations have an effect, and fish data from auxiliary systems such as stationary sonars. Extension of vehicle models themselves and/or adaptation of hybrid type of methods incorporating structure and fish models (e.g., reaching the formulation of fish–machine interaction concept) could also benefit farm automation through Digital Twin concepts.

4.3.5. Module integration

A setup such as the one used by Su et al. (2021) could represent a starting point for developing a Digital Twin in this field (see e.g., Fig. 8). As for the other two cases, this would require enabling the real-time transfer of data from the cage to the model, which would mainly be a technical task (e.g., based on the emerging IoT technologies). Furthermore, the system model would need to be expanded with models of the vehicle and the fish at the site, and potentially be equipped with possibilities for dynamic model adjustments based on measurements of e.g., fouling level and current speeds. A data driven model able to predict fish responses to vehicle manoeuvres could be incorporated as a distinct module in the fish model, and be used to perturb the fish behaviour accordingly when a vehicle is nearby. However, if sufficient data could be collected on this aspect, the data driven model could also be used to derive a knowledge based mathematical model of this particular dynamics. This could be done by running simulations of the cases for which there is data, and experiments with various parameter settings to see if it is possible to reproduce the responses. Under the assumption that the simulated fish have a similar set of perception abilities as real fish, this could result in a better understanding in how fish perceive and respond to vehicles in the cage. These elements could then be linked with an interface providing a view of the outputs form the navigation system, sensors, cameras and models.

4.3.6. Industrial applications

A Digital Twin able to reflect the kinematics and dynamics of vehicle operations within a sea-cage could represent a means for an operator to have a better overview of the situation in the cage while conducting real operations. This can be of great help when operating the vehicle, as it would then be easier to orient and conduct operations more precisely, and possibly preempt and avoid unwanted events such as collisions with the net or fish. The Digital Twin could also be used as a basis for a simulator system for training personnel in using underwater vehicles/robots at fish farms. Candidates could then exploit the predictive powers of the models featured in the Digital Twin, and conduct the preliminary stages of training in a purely virtual environment, thereby both reducing the risk and cost at training new operators. As an extension of this, a Digital Twin within this sphere could also be used as a virtual laboratory to test new control approaches in a realistic, albeit purely digital environment. This would allow developing and testing methods/approaches considered too risky to prototype and test in real fish farms, and could hence expand the control system toolbox available for automating fish farm operations. Although this application would only use the simulator part of the Digital Twin, it illustrates that this technology could also be crucial tools in developing the methods needed to enable unmanned fish farm operations in the future.

5. Conclusion and future work

5.1. Digital twins in aquaculture: More fish on the double or double the trouble?

Digital Twin technology has arisen to become a key enabling technology in the realisation of the aims of the Industry 4.0 paradigm of increased digitisation and smarter automation. Several industrial (e.g., manufacturing, process technology, transportation, energy production) and societal (e.g., health care, meteorology, education) segments are already using Digital Twins (Rasheed et al., 2020). However, there is still a vast potential in the application of this technology to new areas, particularly where there are applications that require the combination of models and data streams founded in different scientific disciplines. The marine environment is one such area, and several bodies including the European Research Council (ERC) have recently highlighted the development of Digital Twins of the ocean as a key strategic research direction. This has spawned several ongoing research activities aiming to build Digital Twins of the oceans or parts of the ocean by e.g., combining real-time marine and maritime data with oceanographic models. However, although most applications within aquaculture are inherently of a trans-disciplinary nature, there have been few attempts at developing complete Digital Twin solutions for aquaculture purposes. We therefore set out to examine the potential of developing Digital Twins for this sector in light of the current state-of-the-art and probable future developments.

One important aspect we did not cover in detail in the case studies is the digitisation footprint of the proposed applications, which refers to the assessment of the data storage requirements of applications within digitisation in agriculture (Marinello et al., 2019). This concept has recently been used to explore the development in storage requirements for a 22 ha field over two decades, and how this is expected to develop in the future (Kayad et al., 2022). Similar considerations will also be needed for aquaculture applications for the industry to assess the technical requirements for storage capacity (and possibly processing power) associated with running a Digital Twin for a farming site. It would then make sense to consider the digitisation footprint per unit weight produced (e.g., per tonne) rather than per unit area, as the production yield in aquaculture is less tightly linked with area than in agriculture. At present, the level of development within Digital Twins for aquaculture is too immature, and the industrial application of such solutions too sparse, to conduct assessments at a similar level of detail as Kayad et al. (2022). However, it is possible to make some general approximations based on the components required for such solutions. The mathematical models proposed in the three case studies would contribute to the digitisation footprint as they would require both storage space and memory when continuously running, and the scale of this requirement depends on the model type. For instance, the requirements for individual based models would mainly depend on the number of individuals simulated, while the footprint of Eulerian type models (such as feed distribution and oxygen models) would mainly depend on the spatial extent and resolution of the modelled area. This implies that a trade-off between the extent of the digitisation footprint and the fidelity of the models would be a necessary element in the design of a Digital Twin for aquaculture. The data collection schemes proposed in the case studies would likewise contribute to the footprint as some monitoring methods such as active acoustics and camera based solutions tend to generate large amounts of data (often several gigabytes per day, depending on sampling frequency). However, this footprint could be severely reduced by processing and interpreting the data before storage and use in the Digital Twin. For instance, storing time series describing e.g., the spatial distribution with a lower resolution in time and space than that used by the echo sounders rather than raw acoustic data would reduce the data size by orders of magnitude. Similarly, time series describing e.g., the swimming speed or wound frequency over time derived using computer vision would require significantly lower storage space than raw camera footage. Such pre-processing before storage and assimilation into the Digital Twin would also reduce the load on the communication channel between the farm and the Digital Twin. Moreover, storing and using processed data from such sources also makes more sense from a practical perspective, as raw data would be harder and less useful to assimilate into the Digital Twin than interpretations of these data that contain information about core aspects in the dynamics described by the Digital Twin.

To conclude this segment, we review the research questions posed initially in this study:

Research question 1. : by reviewing similar initiatives in other sectors, the approach described in Section 2 seems like a promising candidate for implementing a Digital Twin for aquaculture purposes. The selection of components required and the capability levels identified for the chosen approach appears to be sufficient to fulfil the potential roles of a Digital Twin in aquaculture. This is further illustrated through the case studies in Section 4 as these illustrate how Digital Twin technology can be used to address concrete industrial challenges.

Research question 2. : the current state of the art contains several of the components needed to reach the goal of achieving a Digital Twin for aquaculture. As highlighted in the literature surveys presented in Section 3, there exist several sensor technologies and instruments for acquiring data from fish in aquaculture. While some of these have yet to be applied to aquaculture, their proof of concept for fish in other settings (e.g., wild fish, fisheries) show that they can be used to provide insights into the dynamics of farmed fish. We also identified several knowledge based models describing various aspects of the processes in aquaculture facilities. While most of these models are standalone in the sense that they do not combine aspects from different domains (e.g., biology and structural dynamics), their integration is an ongoing process as evident from recently published studies.

Research question 3. : both the literature survey and the case studies highlight that there are several knowledge gaps that need to be filled before we can claim that a full fledged Digital Twin for aquaculture is possible. However, some of these can possibly be patched temporarily through the application of hybrid analysis methods where data driven modelling approaches are used to fill in the gaps where knowledge based models are not sufficient or do not have the sufficiently fidelity.

Research question 4. : the case studies presented in Section 4 describe potential pathways toward creating Digital Twins for aquaculture. While these do not cover all potential application areas for Digital Twins in aquaculture, our intention was to provide a relevant subset of such applications to illustrate how it could be done. The approach we used to explore the case studies can also be considered a possible first step in developing Digital Twins for specific applications in aquaculture. By systematically identifying existing components and knowledge gaps before starting Digital Twin development, it is likely that the outcome will become more valuable in the end.

5.2. The way onward

A natural track for the way onward in the realisation of Digital Twin technology in aquaculture will be to focus on the knowledge gaps identified above, i.e., the development of missing components, integration of components, and continued validation of these to ensure sufficient fidelity. This suggests that the path towards achieving Digital Twins in aquaculture will be incremental rather than disruptive, in that we can build new solutions on past results and achievements. In parallel with these scientific advances, new innovations in aquaculture technology utilise and build on such results. These industrial developments will likely support further research by raising the industry's awareness and interest in the approach and providing richer datasets through improved and more comprehensive sensor use. Since most research and innovation processes are incremental by nature, a shift to focusing on

Digital Twin development is therefore unlikely to entail a substantial change in how these processes are conducted in science and industry. This is also reflected in the three concrete concepts we highlight in this study, as most of the components proposed for the Digital Twins in those areas already exist in some form. The concepts also illustrate some potential industrial benefits to introducing Digital Twins in these areas, and it is clear that similar benefits could be achieved in other areas within aquaculture. However, it is also important to keep in mind that the three case studies presented here mostly rely upon the abilities of Digital Twins considered to be at the predictive capability level. With time, it is likely that needs for Digital Twins at higher capability levels be required also in aquaculture, e.g., to achieve autonomous production in areas and situations that render human presence at the farm difficult.

The main conclusion of this study is that the technological level within aquaculture is sufficiently high to warrant starting the work on adapting Digital Twins. Furthermore, given the potential benefits, this is a path the scientific community and industry alike should start following. This requires that research and development processes are adjusted to not only focus on their specific goals, but also on how the outcomes will fit in a holistic Digital Twin solution down the line. If we can integrate this vision into the future of research and innovation in aquaculture, it is likely that the future will see us able to harvest the benefits of Digital Twin technology also within this sector.

CRediT authorship contribution statement

Martin Føre: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **Morten Omholt Alver:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Jo Arve Alfredsen:** Writing – review & editing, Writing – original draft, Investigation. **Adil Rasheed:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Thor Hukkelås:** Writing – review & editing, Investigation. **Hans V. Bjelland:** Writing – review & editing, Investigation. **Biao Su:** Writing – review & editing, Investigation. **Sveinung J. Ohrem:** Writing – review & editing, Investigation. **Eleni Kelasidi:** Writing – review & editing, Investigation. **Tomas Norton:** Writing – review & editing, Investigation, Conceptualization. **Nikos Papandroulakis:** Writing – review & editing, Investigation.

Declaration of competing interest

This work has been conducted by the authors through their positions at their respective institutions and all funding used to cover the expenses and time has been acquired from governmental agencies. We declare that we have no economic interests, patents or copyrights that are relevant for this publication.

Data availability

No data was used for the research described in the article.

Acknowledgements

Martin Føre acknowledges the financial support from Salmar ASA/Salmar Aker Ocean AS. This work was partly funded by the Research Council of Norway (RCN) project: CHANGE (no. 313737).

References

Abdel-Tawwab, M., Monier, M.N., Hoseinifar, S.H., Faggio, C., 2019. Fish response to hypoxia stress: growth, physiological, and immunological biomarkers. Fish Physiol. Biochem. 45 (3), 997–1013.
Ahmed, A., Zulfiqar, S., Ghandar, A., Chen, Y., Hanai, M., Theodoropoulos, G., 2019. Digital twin technology for aquaponics: Towards optimizing food production with dynamic data driven application systems. In: Asian Simulation Conference. Springer, pp. 3–14.
Alver, M.O., Alfredsen, J.A., Øie, G., Storøy, W., Olsen, Y., 2010. Automatic control of growth and density in rotifer cultures. Aquac. Eng. 43 (1), 6–13.
Alver, M.O., Alfredsen, J.A., Olsen, Y., 2006. An individual-based population model for rotifer (Brachionus plicatilis) cultures. Hydrobiologia 560 (1), 93–108.
Alver, M.O., Alfredsen, J.A., Sigholt, T., 2004. Dynamic modelling of pellet distribution in Atlantic salmon (*Salmo salar* L.) cages. Aquacult. Eng. 31, 51–72.
Alver, M.O., Føre, M., Alfredsen, J.A., 2022. Predicting oxygen levels in Atlantic salmon (Salmo salar) sea cages. Aquaculture 548, 737720.
Alver, M.O., Føre, M., Alfredsen, J.A., 2023. Effect of cage size on oxygen levels in Atlantic salmon sea cages: A model study. Aquaculture 562, 738831. http://dx.doi.org/10.1016/j.aquaculture.2022.738831.
Alver, M.O., Skøien, K.R., Føre, M., Aas, T.S., Oehme, M., Alfredsen, J.A., 2016. Modelling of surface and 3D pellet distribution in Atlantic salmon (Salmo salar L.) cages. Aquac. Eng. 72, 20–29.
Amundsen, H.B., Caharija, W., Pettersen, K.Y., 2022. Autonomous ROV inspections of aquaculture net pens using DVL. IEEE J. Ocean. Eng. 47 (1), 1–19. http://dx.doi.org/10.1109/JOE.2021.3105285.
An, D., Hao, J., Wei, Y., Wang, Y., Yu, X., 2021. Application of computer vision in fish intelligent feeding system—A review. Aquacult. Res. 52 (2), 423–437. http://dx.doi.org/10.1111/are.14907.
Arrhenius, F., Benneheij, B.J., Rudstam, L.G., Boisclair, D., 2000. Can stationary bottom split-beam hydroacoustics be used to measure fish swimming speed in situ? Fish. Res. 45 (1), 31–41.
Aunsmo, A., Krontveit, R., Valle, P.S., Bohlin, J., 2014. Field validation of growth models used in Atlantic salmon farming. Aquaculture 428–429, 249–257. http://dx.doi.org/10.1016/j.aquaculture.2014.03.007.
Balchen, J.G., 1979. Modeling, prediction, and control of fish behavior. In: Control and Dynamic Systems, vol. 15, Elsevier, pp. 99–146.
Balchen, J.G., 2000. Thirty years of research on the application of cybernetic methods in fisheries and aquaculture technology.
Berckmans, D., 2017. General introduction to precision livestock farming. Animal Front. 7 (1), 6–11. http://dx.doi.org/10.2527/af.2017.0102.
Berthelsen, K., 2017. Ocean Farm 1 becomes a floating laboratory. https://www.fishfarmingexpert.com/article/ocean-farm-1-becomes-a-floating-laboratory/. (Accessed 05 October 2021).
Bjelland, H.V., Føre, M., Lader, P., Kristiansen, D., Holmen, I.M., Fredheim, A., Grøtli, E.I., Fathi, D.E., Oppedal, F., Utne, I.B., et al., 2015. Exposed aquaculture in Norway. In: OCEANS 2015-MTS/IEEE Washington. IEEE, pp. 1–10.
Bjordal, Å., EJuell, J., Lindem, T., Fernö, A., 2020. Hydroacoustic monitoring and feeding control in cage rearing of Atlantic salmon (Salmo salar L.). In: Fish Farming Technology. CRC Press, pp. 203–208.
Björnsson, B., Steinarsson, A., Árnason, T., 2007. Growth model for Atlantic cod (Gadus morhua): Effects of temperature and body weight on growth rate. Aquaculture 271 (1–4), 216–226.
Brijs, J., Føre, M., Gräns, A., Clark, T., Axelsson, M., Johansen, J., 2021. Bio-sensing technologies in aquaculture: how remote monitoring can bring us closer to our farm animals. Phil. Trans. R. Soc. B 376 (1830), 20200218.
Brijs, J., Sandblom, E., Axelsson, M., Sundell, K., Sundh, H., Huyben, D., Broström, R., Kiessling, A., Berg, C., Gräns, A., 2018. The final countdown: Continuous physiological welfare evaluation of farmed fish during common aquaculture practices before and during harvest. Aquaculture 495, 903–911. http://dx.doi.org/10.1016/j.aquaculture.2018.06.081.
Brijs, J., Sandblom, E., Axelsson, M., Sundell, K., Sundh, H., Kiessling, A., Berg, C., Gräns, A., 2019. Remote physiological monitoring provides unique insights on the cardiovascular performance and stress responses of freely swimming rainbow trout in aquaculture. Sci. Rep. 9 (1), 9090. http://dx.doi.org/10.1038/s41598-019-45657-3.
Broch, O.J., Klebert, P., Michelsen, F.A., Alver, M.O., 2020. Multiscale modelling of cage effects on the transport of effluents from open aquaculture systems. PLoS One 15 (3), e0228502.
Burke, M., Grant, J., Filgueira, R., Stone, T., 2021. Oceanographic processes control dissolved oxygen variability at a commercial Atlantic salmon farm: Application of a real-time sensor network. Aquaculture 533, 736143.
Chahid, A., N'Doye, I., Majoris, J.E., Berumen, M.L., Laleg-Kirati, T.M., 2022. Fish growth trajectory tracking using Q-learning in precision aquaculture. Aquaculture 550, 737838. http://dx.doi.org/10.1016/j.aquaculture.2021.737838.
Chalikov, D., 1978. The numerical simulation of wind-wave interaction. J. Fluid Mech. 87 (3), 561–582.
Chatziantoniou, A., Charalampis Spondylidis, S., Stavrakidis-Zachou, O., Papandroulakis, N., Topouzelis, K., 2022. Dissolved oxygen estimation in aquaculture sites using remote sensing and machine learning. Remote Sens. Appl. Soc. Environ. 28, 100865. http://dx.doi.org/10.1016/j.rsase.2022.100865.
Chen, Y., Jackson, D., Harvey, H., 1992. A comparison of von Bertalanffy and polynomial functions in modelling fish growth data. Can. J. Fish. Aquat. Sci. 49 (6), 1228–1235.
Chen, L., Yang, X., Sun, C., Wang, Y., Xu, D., Zhou, C., 2020. Feed intake prediction model for group fish using the MEA-BP neural network in intensive aquaculture. Inf. Process. Agric. 7 (2), 261–271.
Chiariotti, P., Martarelli, M., Castellini, P., 2019. Acoustic beamforming for noise source localization – Reviews, methodology and applications. Mech. Syst. Signal Process. 120, 422–448. http://dx.doi.org/10.1016/j.ymssp.2018.09.019.

Cho, C.Y., Bureau, D.P., 1998. Development of bioenergetic models and the Fish-PrFEQ software to estimate production, feeding ration and waste output in aquaculture. Aquat. Living Resour. 11 (4), 199–210.

Cisar, P., Bekkozhayeva, D., Movchan, O., Saberioon, M., Schraml, R., 2021. Computer vision based individual fish identification using skin dot pattern. Sci. Rep. 11 (1), 1–12.

Cotter, E., Polagye, B., 2020. Automatic classification of biological targets in a tidal channel using a multibeam sonar. J. Atmos. Ocean. Technol. 37 (8), 1437–1455. http://dx.doi.org/10.1175/JTECH-D-19-0222.1.

Cuenco, M.L., Stickney, R.R., Grant, W.E., 1985. Fish bioenergetics and growth in aquaculture ponds: II. Effects of interactions among, size, temperature, dissolved oxygen, unionized ammonia and food on growth of individual fish. Ecol. Model. 27 (3–4), 191–206.

Difford, G.F., Boison, S.A., Khaw, H.L., Gjerde, B., 2020. Validating non-invasive growth measurements on individual Atlantic salmon in sea cages using diode frames. Comput. Electron. Agric. 173, 105411.

DNV GL, 2021. Nautical Site Information Models (NSIM). https://www.dnv.com/services/nautical-site-information-models-nsim--86364. (Accessed 05 October 2021).

Dong, G.H., Tang, M.F., Xu, T.J., Bi, C.W., Guo, W.J., 2019. Experimental analysis of the hydrodynamic force on the net panel in wave. Appl. Ocean Res. 87, 233–246.

Dong, G.H., Xu, T.J., Zhao, Y.P., Li, Y.C., Gui, F.K., 2010. Numerical simulation of hydrodynamic behavior of gravity cage in irregular waves. Aquac. Eng. 42 (2), 90–101.

Elfarri, E.M., Rasheed, A., San, O., 2023. Artificial intelligence-driven digital twin of a modern house demonstrated in virtual reality. IEEE Access 11, 35035–35058. http://dx.doi.org/10.1109/ACCESS.2023.3265191.

Endo, H., Wu, H., 2019. Biosensors for the assessment of fish health: A review. Fish. Sci. 85 (4), 641–654. http://dx.doi.org/10.1007/s12562-019-01318-y.

Endresen, P.C., Føre, M., Fredheim, A., Kristiansen, D., Enerhaug, B., 2013. Numerical modeling of wake effect on aquaculture nets. In: International Conference on Offshore Mechanics and Arctic Engineering, Vol. 55355. American Society of Mechanical Engineers, p. V003T05A027.

Erikson, U., Gansel, L., Frank, K., Svendsen, E., Digre, H., 2016. Crowding of Atlantic salmon in net-pen before slaughter. Aquaculture 465, 395–400.

Evensen, G., et al., 2009. Data Assimilation: The Ensemble Kalman Filter, vol. 2, Springer.

FAO, 2022. Food and Agriculture Organization of the United Nations: Aquaculture production: quantities 1950–2019. Available from http://www.fao.org/fishery/en. (Accessed 25 April 2022).

Folkedal, O., Stien, L.H., Nilsson, J., Torgersen, T., Fosseidengen, J.E., Oppedal, F., 2012. Sea caged Atlantic salmon display size-dependent swimming depth. Aquat. Living Resour. 25 (2), 143–149.

Føre, M., Alfredsen, J.A., Gronningsater, A., 2011. Development of two telemetry-based systems for monitoring the feeding behaviour of Atlantic Salmon (Salmo Salar L.) in aquaculture sea-cages. Comput. Electron. Agric. 76 (2), 240–251. http://dx.doi.org/10.1016/j.compag.2011.02.003.

Føre, M., Alver, M., Alfredsen, J.A., Marafioti, G., Senneset, G., Birkevold, J., Willumsen, F.V., Lange, G., Espmark, Å., Terjesen, B.F., 2016. Modelling growth performance and feeding behaviour of Atlantic salmon (Salmo salar L.) in commercial-size aquaculture net pens: Model details and validation through full-scale experiments. Aquaculture 464, 268–278.

Føre, M., Dempster, T., Alfredsen, J.A., Johansen, V., Johansson, D., 2009. Modelling of Atlantic salmon (*Salmo salar* L.) behaviour in sea-cages: A Lagrangian approach. Aquaculture 288, 196–204.

Føre, M., Frank, K., Dempster, T., Alfredsen, J.A., Høy, E., 2017. Biomonitoring using tagged sentinel fish and acoustic telemetry in commercial salmon aquaculture: A feasibility study. Aquac. Eng. 78, 163–172. http://dx.doi.org/10.1016/j.aquaeng.2017.07.004.

Føre, M., Frank, K., Norton, T., Svendsen, E., Alfredsen, J.A., Dempster, T., Eguiraun, H., Watson, W., Stahl, A., Sunde, L.M., Schellewald, C., Skøien, K.R., Alver, M.O., Berckmans, D., 2018. Precision fish farming: a new framework to improve production in aquaculture. Biosyst. Eng. 173, 176–193.

Forsberg, O., 1997. The impact of varying feeding regimes on oxygen consumption and excretion of carbon dioxide and nitrogen in post-smolt Atlantic salmon Salmo salar L.. Aquacult. Res. 28 (1), 29–41.

Fossen, T.I., 1999. Guidance and Control of Ocean Vehicles (Doctors thesis). University of Trondheim, Norway, Printed by John Wiley & Sons, Chichester, England, ISBN: 0 471 94113 1.

Fredriksson, D.W., DeCew, J.C., Tsukrov, I., Swift, M., Irish, J.D., 2007. Development of large fish farm numerical modeling techniques with in situ mooring tension comparisons. Aquac. Eng. 36 (2), 137–148.

Fredriksson, D.W., Swift, M.R., Irish, J.D., Tsukrov, I., Celikkol, B., 2003. Fish cage and mooring system dynamics using physical and numerical models with field measurements. Aquac. Eng. 27 (2), 117–146.

Gansel, L., Bloecher, N., Floerl, O., Guenther, J., 2017. Quantification of biofouling on nets: a comparison of wet weight measurements and optical (image analysis) methods. Aquac. Int. 25 (2), 679–692.

Gansel, L.C., Oppedal, F., Birkevold, J., Tuene, S.A., 2018. Drag forces and deformation of aquaculture cages—Full-scale towing tests in the field. Aquac. Eng. 81, 46–56.

Georgopoulou, D.G., Fanouraki, E., Voskakis, D., Mitrizakis, N., Papandroulakis, N., 2022. European seabass show variable responses in their group swimming features after tag implantation. Front. Animal Sci. 3.

Georgopoulou, D.G., Stavrakidis-Zachou, O., Mitrizakis, N., Papandroulakis, N., 2021. Tracking and analysis of the movement behavior of European seabass (Dicentrarchus Labrax) in aquaculture systems. Front. Animal Sci. 2.

Ghandar, A., Ahmed, A., Zulfiqar, S., Hua, Z., Hanai, M., Theodoropoulos, G., 2021. A decision support system for urban agriculture using digital twin: A case study with aquaponics. IEEE Access 9, 35691–35708.

Hao, M., Yu, H., Li, D., 2015. The measurement of fish size by machine vision-a review. In: International Conference on Computer and Computing Technologies in Agriculture. Springer, pp. 15–32.

Hassan, W., Føre, M., Pedersen, M.O., Alfredsen, J.A., 2020. A new method for measuring free-ranging fish swimming speed in commercial marine farms using Doppler principle. IEEE Sens. J. 20 (17), 10220–10227. http://dx.doi.org/10.1109/JSEN.2020.2991294.

Haugaløkken, B.O.A., Sandøy, S.S., Schjølberg, I., Alfredsen, J.A., Utne, I.B., 2018. Probabilistic localization and mapping of flexible underwater structures using octomap. In: European Control Conference 2018. Limassol, Cyprus, Institute of Electrical and Electronics Engineers (IEEE), pp. 268–275. http://dx.doi.org/10.23919/ECC.2018.8550498.

Hvas, M., Folkedal, O., Oppedal, F., 2020. Heart rate bio-loggers as welfare indicators in Atlantic salmon (Salmo Salar) aquaculture. Aquaculture 529, 735630. http://dx.doi.org/10.1016/j.aquaculture.2020.735630.

Hvas, M., Folkedal, O., Oppedal, F., 2021. Fish welfare in offshore salmon aquaculture. Rev. Aquac. 13 (2), 836–852.

Iswari, N.M.S., Wella, Ranny, 2017. Fish freshness classification method based on fish image using K-nearest neighbor. In: 2017 4th International Conference on New Media Studies. CONMEDIA, pp. 87–91. http://dx.doi.org/10.1109/CONMEDIA.2017.8266036.

Jepsen, N., Koed, A., Thorstad, E.B., Baras, E., 2002. Surgical implantation of telemetry transmitters in fish: How much have we learned? Hydrobiologia 483 (1), 239–248. http://dx.doi.org/10.1023/A:1021356302311.

Johansson, D., Ruohonen, K., Kiessling, A., Oppedal, F., Stiansen, J.E., Kelly, M., Juell, J.E., 2006. Effect of environmental factors on swimming depth preferences of Atlantic salmon (Salmo salar L.) and temporal and spatial variations in oxygen levels in sea cages at a fjord site. Aquaculture 254 (1–4), 594–605.

Jones, D., Snider, C., Nassehi, A., Yon, J., Hicks, B., 2020. Characterising the digital twin: A systematic literature review. CIRP J. Manuf. Sci. Technol. 29, 36–52. http://dx.doi.org/10.1016/j.cirpj.2020.02.002.

Jónsdóttir, K.E., Hvas, M., Alfredsen, J.A., Føre, M., Alver, M.O., Bjelland, H.V., Oppedal, F., 2019. Fish welfare based classification method of ocean current speeds at aquaculture sites. Aquac. Environ. Interact. 11, 249–261.

Jopling, J.K., Pridgen, B.C., Yeung, S., 2021. Setting assessment standards for artificial intelligence computer vision wound annotations. JAMA Netw. Open 4 (5), e217851.

Kasumyan, A., 2008. Sounds and sound production in fishes. J. Ichthyol. 48 (11), 981–1030.

Kayad, A., Sozzi, M., Paraforos, D.S., Rodrigues, Jr., F.A., Cohen, Y., Fountas, S., Francisco, M.J., Pezzuolo, A., Grigolato, S., Marinello, F., 2022. How many gigabytes per hectare are available in the digital agriculture era? A digitization footprint estimation. Comput. Electron. Agric. 198, 107080. http://dx.doi.org/10.1016/j.compag.2022.107080.

Kelasidi, E., Su, B., Caharija, W., Føre, M., Pedersen, M.O., Frank, K., 2022. Autonomous monitoring and inspection operations with UUVs in fish farms. IFAC-PapersOnLine 55 (31), 401–408. http://dx.doi.org/10.1016/j.ifacol.2022.10.461.

Kelasidi, E., Svendsen, E., 2022. Robotics for sea-based fish farming. In: Zhang, Q. (Ed.), Encyclopedia of Smart Agriculture Technologies. Springer International Publishing, Cham, pp. 1–20. http://dx.doi.org/10.1007/978-3-030-89123-7_202-1.

Klebert, P., Lader, P., Gansel, L., Oppedal, F., 2013. Hydrodynamic interactions on net panel and aquaculture fish cages: A review. Ocean Eng. 58, 260–274.

Klebert, P., Su, B., 2020. Turbulence and flow field alterations inside a fish sea cage and its wake. Appl. Ocean Res. 98, 102113.

Klebert, P., Volent, Z., Rosten, T., 2018. Measurement and simulation of the three-dimensional flow pattern and particle removal efficiencies in a large floating closed sea cage with multiple inlets and drains. Aquac. Eng. 80, 11–21.

Knudsen, F., Fosseidengen, J., Oppedal, F., Karlsen, Ø., Ona, E., 2004. Hydroacoustic monitoring of fish in sea cages: target strength (TS) measurements on Atlantic salmon (Salmo salar). Fisheries research 69 (2), 205–209.

Kolarevic, J., Aas-Hansen, Ø., Espmark, Å., Baeverfjord, G., Terjesen, B.F., Damsgård, B., 2016. The use of acoustic acceleration transmitter tags for monitoring of Atlantic Salmon swimming activity in recirculating aquaculture systems (RAS). Aquac. Eng. 72–73, 30–39. http://dx.doi.org/10.1016/j.aquaeng.2016.03.002.

Komarudin, M., Septama, H., Yulianti, T., Yudamson, A., Hendri, J., Arafat, M., 2021. Multi node sensors for water quality monitoring towards precision aquaculture. In: IOP Conference Series: Earth and Environmental Science, vol. 739, (no. 1), IOP Publishing, 012026.

Kooijman, S.A.L.M., 2000. Dynamic Energy and Mass Budgets in Biological Systems. Cambridge University Press.

Kristiansen, T., Faltinsen, O.M., 2015. Experimental and numerical study of an aquaculture net cage with floater in waves and current. J. Fluids Struct. 54, 1–26.

Kruusmaa, M., Gkliva, R., Tuhtan, J.A., Tuvikene, A., Alfredsen, J.A., 2020. Salmon behavioural response to robots in an aquaculture sea cage. Royal Soc. Open Sci. 7 (3), 191220. http://dx.doi.org/10.1098/rsos.191220.

Lader, P., Dempster, T., Fredheim, A., Jensen, Ø., 2008. Current induced net deformations in full-scale sea-cages for Atlantic salmon (Salmo salar). Aquac. Eng. 38 (1), 52–65.

Lader, P., Kristiansen, D., Alver, M., Bjelland, H.V., Myrhaug, D., 2017. Classification of aquaculture locations in Norway with respect to wind wave exposure. In: International Conference on Offshore Mechanics and Arctic Engineering, Vol. 57724. American Society of Mechanical Engineers, p. V006T05A005.

Lien, A.M., Schellewald, C., Stahl, A., Frank, K., Skøien, K.R., Tjølsen, J.I., 2019. Determining spatial feed distribution in sea cage aquaculture using an aerial camera platform. Aquac. Eng. 87, 102018.

Lika, K., Papandroulakis, N., 2005. Modeling feeding processes: A test of a new model for sea bream (Sparus Aurata) larvae. Can. J. Fish. Aquat. Sci. 62 (2), 425–435. http://dx.doi.org/10.1139/f04-198.

Lima, A.C., Royer, E., Bolzonella, M., Pastres, R., 2022. Digital twins for land-based aquaculture: A case study for rainbow trout (Oncorhynchus Mykiss). Open Res. Eur. 2 (16), 16.

Livanos, G., Zervakis, M., Chalkiadakis, V., Moirogiorgou, K., Giakos, G., Papandroulakis, N., 2018. Intelligent navigation and control of a prototype autonomous underwater vehicle for automated inspection of aquaculture net pen cages. In: 2018 IEEE International Conference on Imaging Systems and Techniques. IST, IEEE, pp. 1–6.

Løland, G., 1993. Current forces on, and water flow through and around, floating fish farms. Aquac. Int. 1 (1), 72–89.

Macaulay, G., Warren-Myers, F., Barrett, L.T., Oppedal, F., Føre, M., Dempster, T., 2021. Tag use to monitor fish behaviour in aquaculture: A review of benefits, problems and solutions. Rev. Aquac. 13 (3), 1565–1582. http://dx.doi.org/10.1111/raq.12534.

Madshaven, A., Schellewald, C., Stahl, A., 2022. Hole detection in aquaculture net cages from video footage. In: Fourteenth International Conference on Machine Vision, Vol. 12084. ICMV 2021, SPIE, pp. 258–267.

Måløy, H., 2020. EchoBERT: A transformer-based approach for behavior detection in echograms. IEEE Access 8, 218372–218385.

Måløy, H., Aamodt, A., Misimi, E., 2019. A spatio-temporal recurrent network for salmon feeding action recognition from underwater videos in aquaculture. Comput. Electron. Agric. 167, 105087.

Marinello, F., Bramley, R., Cohen, Y., Fountas, S., Guo, H., Karkee, M., Martínez-Casasnovas, J., Paraforos, D., Sartori, L., Sorensen, C., et al., 2019. Agriculture and digital sustainability: a digitization footprint. In: Precision Agriculture'19. Wageningen Academic Publishers, pp. 4–18.

Mathisen, B.M., Bach, K., Aamodt, A., 2021. Using extended siamese networks to provide decision support in aquaculture operations. Appl. Intell. 51 (11), 8107–8118. http://dx.doi.org/10.1007/s10489-021-02251-3.

Mathisen, B.M., Haro, P., Hanssen, B., Björk, S., Walderhaug, S., 2016. Decision support systems in fisheries and aquaculture: A systematic review. arXiv preprint arXiv:1611.08374.

McIntosh, P., Barrett, L.T., Warren-Myers, F., Coates, A., Macaulay, G., Szetey, A., Robinson, N., White, C., Samsing, F., Oppedal, F., Folkedal, O., Klebert, P., Dempster, T., 2022. Supersizing salmon farms in the coastal zone: A global analysis of changes in farm technology and location from 2005 to 2020. Aquaculture 553, 738046. http://dx.doi.org/10.1016/j.aquaculture.2022.738046.

Medaas, C., Lien, M.E., Gismervik, K., Kristiansen, T.S., Osmundsen, T., Størkersen, K.V., Tørud, B., Stien, L.H., 2021. Minding the gaps in fish welfare: The untapped potential of fish farm workers. J. Agric. Environ. Ethics 34 (5), 29. http://dx.doi.org/10.1007/s10806-021-09869-w.

Michelsen, F.A., Klebert, P., Broch, O.J., Alver, M.O., 2019. Impacts of fish farm structures with biomass on water currents: A case study from Frøya. J. Sea Res. 154, 101806.

Moe, H., Fredheim, A., Hopperstad, O.S., 2010. Structural analysis of aquaculture net cages in current. J. Fluids Struct. 26 (3), 503–516.

Moe-Føre, H., Lader, P., Lien, E., Hopperstad, O., 2016. Structural response of high solidity net cage models in uniform flow. J. Fluids Struct. 65, 180–195.

Moe Føre, H., Thorvaldsen, T., 2021. Causal analysis of escape of Atlantic salmon and rainbow trout from Norwegian fish farms during 2010–2018. Aquaculture 532, 736002. http://dx.doi.org/10.1016/j.aquaculture.2020.736002.

Moe Føre, H., Thorvaldsen, T., Osmundsen, T.C., Asche, F., Tveterås, R., Fagertun, J.T., Bjelland, H.V., 2022. Technological innovations promoting sustainable salmon (Salmo Salar) aquaculture in Norway. Aquac. Rep. 24, 101115. http://dx.doi.org/10.1016/j.aqrep.2022.101115.

Moore, A.M., Arango, H.G., Broquet, G., Powell, B.S., Weaver, A.T., Zavala-Garay, J., 2011. The Regional Ocean Modeling System (ROMS) 4-dimensional variational data assimilation systems: Part I–System overview and formulation. Prog. Oceanogr. 91 (1), 34–49.

Morro, B., Davidson, K., Adams, T.P., Falconer, L., Holloway, M., Dale, A., Aleynik, D., Thies, P.R., Khalid, F., Hardwick, J., et al., 2022. Offshore aquaculture of finfish: Big expectations at sea. Rev. Aquac. 14 (2), 791–815. http://dx.doi.org/10.1111/raq.12625.

Neethirajan, S., Kemp, B., 2021. Digital livestock farming. Sens. Bio-Sens. Res. 32, 100408.

Nichols, D., Hogan, T., 2022. Remote sensing technologies to monitor harmful algal blooms in offshore aquaculture. World Aquac. 21.

Nisbet, R.M., Jusup, M., Klanjscek, T., Pecquerie, L., 2012. Integrating dynamic energy budget (DEB) theory with traditional bioenergetic models. J. Exp. Biol. 215 (6), 892–902.

Nobre, A.M., Valente, L.M., Conceição, L., Severino, R., Lupatsch, I., 2019. A bioenergetic and protein flux model to simulate fish growth in commercial farms: Application to the gilthead seabream. Aquac. Eng. 84, 12–22.

O'Donncha, F., Grant, J., 2019. Precision aquaculture. IEEE Internet Things Mag. 2 (4), 26–30. http://dx.doi.org/10.1109/IOTM.0001.1900033.

Ohrem, S.J., Amundsen, H.B., Kelasidi, E., 2021. Control-oriented modeling of an underwater biofouling prevention robot. In: 2021 20th International Conference on Advanced Robotics. ICAR, IEEE, pp. 1121–1128.

Oppedal, F., Bui, S., Stien, L.H., Overton, K., Dempster, T., 2019. Snorkel technology to reduce sea lice infestations: Efficacy depends on salinity at the farm site, but snorkels have minimal effects on salmon production and welfare. Aquac. Environ. Interact. 11, 445–457. http://dx.doi.org/10.3354/aei00321.

Oppedal, F., Dempster, T., Stien, L.H., 2011. Environmental drivers of Atlantic salmon behaviour in sea-cages: A review. Aquaculture 311 (1), 1–18. http://dx.doi.org/10.1016/j.aquaculture.2010.11.020.

Oppedal, F., Juell, J.E., Tarranger, G., Hansen, T., 2001. Artificial light and season affects vertical distribution and swimming behaviour of post-smolt Atlantic salmon in sea cages. J. Fish Biol. 58 (6), 1570–1584.

Ouyang, B., Wills, P.S., Tang, Y., Hallstrom, J.O., Su, T.C., Namuduri, K., Mukherjee, S., Rodriguez-Labra, J.I., Li, Y., Den Ouden, C.J., 2021. Initial development of the Hybrid Aerial Underwater Robotic System (HAUCS): Internet of Things (IoT) for aquaculture farms. IEEE Internet Things J. 8 (18), 14013–14027. http://dx.doi.org/10.1109/JIOT.2021.3068571.

Palaiokostas, C., 2021. Predicting for disease resistance in aquaculture species using machine learning models. Aquac. Rep. 20, 100660. http://dx.doi.org/10.1016/j.aqrep.2021.100660.

Palomares, M.L., Pauly, D., 1989. A multiple regression model for prediction the food consumption of marine fish populations. Mar. Freshwater Res. 40 (3), 259–273. http://dx.doi.org/10.1071/mf9890259.

Papandroulakis, N., Thomsen, C., Mintenbeck, K., Mayorga, P., Hernández-Brito, J.J., 2017. The EU-project "TROPOS". In: Aquaculture Perspective of Multi-Use Sites in the Open Ocean: The Untapped Potential for Marine Resources in the Anthropocene. Springer International Publishing, pp. 355–374.

Pylianidis, C., Osinga, S., Athanasiadis, I.N., 2021. Introducing digital twins to agriculture. Comput. Electron. Agric. 184, 105942. http://dx.doi.org/10.1016/j.compag.2020.105942.

Ramos, L., 2021. How Digital Twin could double down farm efficiency. https://www.aquaculturenorthamerica.com/how-digital-twin-could-double-down-farm-efficiency/. (Accessed 05 October 2021).

Rasheed, A., San, O., Kvamsdal, T., 2019. Hybrid analysis and modeling as an enabler for big data cybernetics. In: Proceedings of the 32nd Nordic Seminar on Computational Mechanics. Oulu, Finland, pp. 24–25.

Rasheed, A., San, O., Kvamsdal, T., 2020. Digital twin: Values, challenges and enablers from a modeling perspective. IEEE Access 8, 21980–22012. http://dx.doi.org/10.1109/ACCESS.2020.2970143.

Reite, K.J., Føre, M., Aarsæther, K.G., Jensen, J., Rundtop, P., Kyllingstad, L.T., Endresen, P.C., Kristiansen, D., Johansen, V., Fredheim, A., 2014. FHSIM — Time Domain Simulation of Marine Systems. In: International Conference on Offshore Mechanics and Arctic Engineering. In: Ocean Engineering, vol. 8A, http://dx.doi.org/10.1115/OMAE2014-23165, p. V08AT06A014.

Remen, M., Oppedal, F., Imsland, A.K., Olsen, R.E., Torgersen, T., 2013. Hypoxia tolerance thresholds for post-smolt Atlantic salmon: Dependency of temperature and hypoxia acclimation. Aquaculture 416–417, 41–47. http://dx.doi.org/10.1016/j.aquaculture.2013.08.024.

Remen, M., Oppedal, F., Torgersen, T., Imsland, A.K., Olsen, R.E., 2012. Effects of cyclic environmental hypoxia on physiology and feed intake of post-smolt Atlantic salmon: Initial responses and acclimation. Aquaculture 326–329, 148–155. http://dx.doi.org/10.1016/j.aquaculture.2011.11.036.

Rosell Moll, E., Piazzon de Haro, M.C., Sosa, J., Ferrer, M., Cabruja, E., Vega Martínez, A., Calduch Giner, J., Sitja-Bobadilla, A., Lozano, M., Montiel-Nelson, J.A., et al., 2021. Smart Biosensing Device for Tracking Fish Behaviour. Universidade do Algarve.

Rosten, C.M., Mathiassen, J.R., Volent, Z., 2023. Acoustic environment of aquaculture net-pens varies with feeding status of Atlantic salmon (Salmo salar). Aquaculture 563, 738949. http://dx.doi.org/10.1016/j.aquaculture.2022.738949.

Rountree, R.A., Juanes, F., Bolgan, M., 2018. Air movement sound production by alewife, white sucker, and four salmonid fishes suggests the phenomenon is widespread among freshwater fishes. PLoS One 13 (9), e0204247. http://dx.doi.org/10.1371/journal.pone.0204247.

Royer, E., Faccenda, F., Pastres, R., 2021. Estimating oxygen consumption of rainbow trout (Oncorhynchus Mykiss) in a raceway: A precision fish farming approach. Aquac. Eng. 92, 102141. http://dx.doi.org/10.1016/j.aquaeng.2020.102141.

Rundtop, P., Frank, K., 2016. Experimental evaluation of hydroacoustic instruments for ROV navigation along aquaculture net pens. Aquac. Eng. 74, 143–156. http://dx.doi.org/10.1016/j.aquaeng.2016.08.002.

Russel, G., 2021. R3-IoT: Digital platform is set to revolutionise aquaculture. https://www.thenational.scot/news/19281879.new-digital-platform-will-revolutionise-aquaculture/. (Accessed 05 October 2021).

Russo, T., Prestinicola, L., Scardi, M., Palamara, E., Cataudella, S., Boglione, C., 2010. Progress in modeling quality in aquaculture: An application of the self-organizing map to the study of skeletal anomalies and meristic counts in Gilthead Seabream (Sparus Aurata, L. 1758). J. Appl. Ichthyol. 26 (2), 360–365. http://dx.doi.org/10.1111/j.1439-0426.2010.01435.x.

Saberioon, M., Gholizadeh, A., Cisar, P., Pautsina, A., Urban, J., 2017. Application of machine vision systems in aquaculture with emphasis on fish: State-of-the-art and key issues. Rev. Aquac. 9 (4), 369–387. http://dx.doi.org/10.1111/raq.12143.

San, O., Rasheed, A., Kvamsdal, T., 2021. Hybrid analysis and modeling, eclecticism, and multifidelity computing toward digital twin revolution. GAMM-Mitt. 44 (2), e202100007. http://dx.doi.org/10.1002/gamm.202100007.

Sara, J.R., Gous, R.M., Bureau, D.P., 2009. Describing growth and predicting feed intake in the marine prawn Fenneropenaeus indicus: Part I: Theoretical and practical aspects of measuring and predicting genetic parameters. Aquaculture 287 (3), 402–413. http://dx.doi.org/10.1016/j.aquaculture.2008.10.057.

Schellewald, C., Stahl, A., Kelasidi, E., 2021. Vision-based pose estimation for autonomous operations in aquacultural fish farms. IFAC-PapersOnLine 54 (16), 438–443. http://dx.doi.org/10.1016/j.ifacol.2021.10.128.

Schleich, B., Anwer, N., Mathieu, L., Wartzack, S., 2017. Shaping the digital twin for design and production engineering. CIRP Ann. 66 (1), 141–144. http://dx.doi.org/10.1016/j.cirp.2017.04.040.

Schraml, R., Hofbauer, H., Jalilian, E., Bekkozhayeva, D., Saberioon, M., Cisar, P., Uhl, A., 2020. Towards fish individuality-based aquaculture. IEEE Trans. Ind. Inform. 17 (6), 4356–4366. http://dx.doi.org/10.1109/TII.2020.3006933.

Shchepetkin, A.F., McWilliams, J.C., 2005. The regional oceanic modeling system (ROMS): A split-explicit, free-surface, topography-following-coordinate oceanic model. Ocean Model. 9 (4), 347–404. http://dx.doi.org/10.1016/j.ocemod.2004.08.002.

Simonnet-Laprade, C., Bayen, S., Le Bizec, B., Dervilly, G., 2021. Data analysis strategies for the characterization of chemical contaminant mixtures. Fish as a case study. Environ. Int. 155, 106610. http://dx.doi.org/10.1016/j.envint.2021.106610.

SINTEF, 2023. HAVOPERA. Available from http://www.sintef.no/laboratorier/havopera. (Accessed 30 June 2023).

SINTEF Ocean, 2020. RACE digital cage. https://www.sintef.no/en/projects/2020/race-digital-cage/. (Accessed 05 October 2021).

Skøien, K.R., Alver, M.O., Alfredsen, J.A., 2014. A computer vision approach for detection and quantification of feed particles in marine fish farms. In: 2014 IEEE International Conference on Image Processing. ICIP, IEEE, pp. 1648–1652.

Slagstad, D., Ellingsen, I.H., Wassmann, P., 2011. Evaluating primary and secondary production in an Arctic Ocean void of summer sea ice: An experimental simulation approach. Prog. Oceanogr. 90 (1), 117–131. http://dx.doi.org/10.1016/j.pocean.2011.02.009.

Slagstad, D., McClimans, T.A., 2005. Modeling the ecosystem dynamics of the Barents sea including the marginal ice zone: I. Physical and chemical oceanography. J. Mar. Syst. 58 (1), 1–18. http://dx.doi.org/10.1016/j.jmarsys.2005.05.005.

Solstorm, D., Oldham, T., Solstorm, F., Klebert, P., Stien, L.H., Vågseth, T., Oppedal, F., 2018. Dissolved oxygen variability in a commercial sea-cage exposes farmed Atlantic salmon to growth limiting conditions. Aquaculture 486, 122–129. http://dx.doi.org/10.1016/j.aquaculture.2017.12.008.

Sreedevi, T., Kumar, M.S., 2020. Digital twin in smart farming: A categorical literature review and exploring possibilities in hydroponics. In: 2020 Advanced Computing and Communication Technologies for High Performance Applications. ACCTHPA, IEEE, pp. 120–124.

Staalesen, K., 2019. Exploring the Digital Twin Concept for a Rigid Aquaculture Cage (Master's thesis). NTNU.

Stadtmann, F., Rasheed, A., Kvamsdal, T., Johannessen, K.A., San, O., Kölle, K., Tande, J.O., Barstad, I., Benhamou, A., Brathaug, T., Christiansen, T., Firle, A.L., Fjeldly, A., Frøyd, L., Gleim, A., Høiberget, A., Meissner, C., Nygård, G., Olsen, J., Paulshus, H., Rasmussen, T., Rishoff, E., Scibilia, F., Skogås, J.O., 2023a. Digital twins in wind energy: Emerging technologies and industry-informed future directions. IEEE Access 11, 110762–110795. http://dx.doi.org/10.1109/ACCESS.2023.3321320.

Stadtmann, F., Wassertheurer, H.A.G., Rasheed, A., 2023b. Demonstration of a standalone, descriptive, and predictive digital twin of a floating offshore wind turbine. In: ASME 2023 42nd International Conference on Ocean, Offshore and Arctic Engineering. American Society of Mechanical Engineers Digital Collection, http://dx.doi.org/10.1115/OMAE2023-103112.

Stavelin, H., Rasheed, A., San, O., Hestnes, A.J., 2021. Applying object detection to marine data and exploring explainability of a fully convolutional neural network using principal component analysis. Ecol. Inform. 62, 101269. http://dx.doi.org/10.1016/j.ecoinf.2021.101269.

Stavrakidis-Zachou, O., Papandroulakis, N., Lika, K., 2019. A DEB model for European sea bass (Dicentrarchus Labrax): Parameterisation and application in aquaculture. J. Sea Res. 143, 262–271. http://dx.doi.org/10.1016/j.seares.2018.05.008.

Stavrakidis-Zachou, O., Papandroulakis, N., Pavlidis, M., Lika, K., 2021. Preliminary dynamic energy budget models for studying the thermal tolerance of E. seabass and meagre. In: Aquaculture Europe 2021. Madeira, Portugal, EAS, pp. 1244–1245.

Stien, L.H., Nilsson, J., Bui, S., Fosseidengen, J.E., Kristiansen, T.S., Øverli, Ø., Folkedal, O., 2017. Consistent melanophore spot patterns allow long-term individual recognition of Atlantic salmon Salmo salar. J. Fish Biol. 91 (6), 1699–1712. http://dx.doi.org/10.1111/jfb.13491.

Stockwell, C.L., Filgueira, R., Grant, J., 2021. Determining the effects of environmental events on cultured Atlantic salmon behaviour using 3-dimensional acoustic telemetry. Front. Animal Sci. 2, http://dx.doi.org/10.3389/fanim.2021.701813.

Su, B., Bjørnson, F.O., Tsarau, A., Endresen, P.C., Ohrem, S.J., Føre, M., Fagertun, J.T., Klebert, P., Kelasidi, E., Bjelland, H.V., 2023. Towards a holistic digital twin solution for real-time monitoring of aquaculture net cage systems. Mar. Struct. 91, 103469. http://dx.doi.org/10.1016/j.marstruc.2023.103469.

Su, B., Kelasidi, E., Frank, K., Haugen, J., Føre, M., Pedersen, M.O., 2021. An integrated approach for monitoring structural deformation of aquaculture net cages. Ocean Eng. 219, 108424. http://dx.doi.org/10.1016/j.oceaneng.2020.108424.

Su, B., Reite, K.J., Føre, M., Aarsæther, K.G., Alver, M.O., Endresen, P.C., Kristiansen, D., Haugen, J., Caharija, W., Tsarau, A., 2019. A multipurpose framework for modelling and simulation of marine aquaculture systems. In: International Conference on Offshore Mechanics and Arctic Engineering, Vol. 58837. American Society of Mechanical Engineers, p. V006T05A002.

Sukhinov, A.I., Chistyakov, A.E., Timofeeva, E.F., Shishenya, A.V., 2013. Mathematical model for Calculating Coastal wave processes. Math. Models Comput. Simul. 5 (2), 122–129. http://dx.doi.org/10.1134/S2070048213020087.

Thorstad, E.B., Rikardsen, A.H., Alp, A., Økland, F., 2013. The use of electronic tags in fish research–an overview of fish telemetry methods. Turk. J. Fish. Aquat. Sci. 13 (5), 881–896.

Tsukrov, I., Eroshkin, O., Fredriksson, D., Swift, M.R., Celikkol, B., 2003. Finite element modeling of net panels using a consistent net element. Ocean Eng. 30 (2), 251–270. http://dx.doi.org/10.1016/S0029-8018(02)00021-5.

Urke, H., Daae, K., Viljugrein, H., Kandal, I., Staalstrøm, A., Jansen, P., 2021. Improvement of aquaculture management practice by integration of hydrodynamic modelling. Ocean & Coastal Management 213, 105849. http://dx.doi.org/10.1016/j.ocecoaman.2021.105849.

Vaidya, S., Ambad, P., Bhosle, S., 2018. Industry 4.0 – A glimpse. Procedia Manuf. 20, 233–238. http://dx.doi.org/10.1016/j.promfg.2018.02.034, 2nd International Conference on Materials, Manufacturing and Design Engineering (iCMMD2017), 11-12 December 2017, MIT Aurangabad, Maharashtra, INDIA.

VanDerHorn, E., Mahadevan, S., 2021. Digital twin: Generalization, characterization and implementation. Decis. Support Syst. 145, 113524. http://dx.doi.org/10.1016/j.dss.2021.113524.

Verdouw, C., Tekinerdogan, B., Beulens, A., Wolfert, S., 2021. Digital twins in smart farming. Agric. Syst. 189, 103046. http://dx.doi.org/10.1016/j.agsy.2020.103046.

von Rueden, L., Mayer, S., Sifa, R., Bauckhage, C., Garcke, J., 2020. Combining machine learning and simulation to a hybrid modelling approach: Current and future directions. In: Advances in Intelligent Data Analysis XVIII: 18th International Symposium on Intelligent Data Analysis, IDA 2020, Konstanz, Germany, April 27–29, 2020, Proceedings 18. Springer, pp. 548–560.

Voskakis, D., Makris, A., Papandroulakis, N., 2021. Deep learning based fish length estimation. An application for the mediterranean aquaculture. In: OCEANS 2021: San Diego–Porto. IEEE, pp. 1–5.

Waldrop, T., Summerfelt, S., Mazik, P., Good, C., 2018. The effects of swimming exercise and dissolved oxygen on growth performance, fin condition and precocious maturation of early-rearing Atlantic salmon Salmo salar. Aquacult. Res. 49 (2), 801–808.

Winthereig-Rasmussen, H., Simonsen, K., Patursson, Ø., 2016. Flow through fish farming sea cages: Comparing computational fluid dynamics simulations with scaled and full-scale experimental data. Ocean Eng. 124, 21–31. http://dx.doi.org/10.1016/j.oceaneng.2016.07.027.

Zacheilas, T., Moirogiorgou, K., Papandroulakis, N., Sotiriades, E., Zervakis, M., Dollas, A., 2021. An FPGA-based system for video processing to detect holes in aquaculture nets. In: 2021 IEEE 21st International Conference on Bioinformatics and Bioengineering. BIBE, IEEE, pp. 1–6.

Zhabitskii, M., Andryenko, Y., Malyshev, V., Chuykova, S., Zhosanov, A., 2021. Digital transformation model based on the digital twin concept for intensive aquaculture production using closed water circulation technology. In: IOP Conference Series: Earth and Environmental Science, vol. 723, (no. 3), IOP Publishing, 032064.

Zhang, H., Wei, Q., Kang, M., 2014. Measurement of swimming pattern and body length of cultured Chinese sturgeon by use of imaging sonar. Aquaculture 434, 184–187. http://dx.doi.org/10.1016/j.aquaculture.2014.08.024.

Zion, B., 2012. The use of computer vision technologies in aquaculture – A review. Comput. Electron. Agric. 88, 125–132. http://dx.doi.org/10.1016/j.compag.2012.07.010.