Precision Aquaculture

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***Abstract*—Precision aquaculture is founded on a set of disparate, interconnected sensors deployed within the marine environment to monitor, analyse, interpret and provide decision support for farm operations. Recent technological innovations facilitate aquaculture becoming part of the Internet of Things (IoT) – modern farms are characterized by hundreds of interconnected sensors which store and serve data, interact with other sensors and devices, and connect with a fog and cloud ecosystem. We describe the implementation of the precision aquaculture concept to a number of farms in eastern Canada. The work combines partners from industry, technology and academia to provide data-driven insight and decision that promotes ecologically sustainable intensification of aquaculture. The paper presents a first case-study on how IoT can instrument, inform, and impact the aquaculture industry. Challenges related to connectivity, interoperability, and standardization are discussed and we elucidate how our experiences can inform future activities.**

Keywords—aquaculture, monitoring, prediction, decision, IoT

I. Introduction

Aquaculture, or the farmed production of fish and shellfish, has grown rapidly, from supplying just seven percent of fish for human consumption in 1974 to more than half in 2016. This rapid expansion has led to challenges including concerns over environmental degradation, disease and parasite outbreaks, and the need to efficiently manage resources to maximize productivity. These factors are pushing farms towards more efficient management practises aimed at the sustainable intensification of the industry. At the same time, innovative technologies are making the collection, processing and analysis of large volumes of heterogeneous datasets possible. Taken together, these two factors are empowering a precision aquaculture framework that combines sensors, cloud and analytics to enable real-time, evidence-based decision making to optimise operations.

Precision aquaculture [1] involves a variety of sensors used to gain insight into the farm environment, make decisions which optimize fish health, growth and economic return, and reduce risk to the environment. This trend parallels developments in agriculture where sensors and other observing technologies lead to enhanced insight into crop health as well as animal welfare. The fundamental approach has been summarised as a series of steps, namely: observe, interpret, decide, and act [1]. Traditionally, many of these steps have required human intervention and depended heavily on farmer experience and intuition for correct decision and action. As farm size increases, however, and move further offshore, automation is imperative to enable economically feasible operations.

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Materialisation of precision aquaculture depends on IoT technologies to empower management in a chaotic environment subject to the vagaries of oceans and weather. An obvious impediment is water cover, but other major obstacles exist, including the harsh environment, power and connectivity in offshore locations, large range of spatial scales involved (fish-, cage-, farm- and bay-scale), and the challenges of manual intervention or analysis in the ocean (where access can be regularly impeded or prevented by adverse weather). A fish farm has an imposing array of underwater chains, ropes, moorings, and other infrastructure, so wireless communications are essential. Further, the distributed nature of the industry, composed of a large number of small-scale aquaculture companies and sensor providers, pose challenges related to the integration of diverse – sometimes proprietary – datasets into a unified edge, fog and cloud ecosystem.

Application of mature monitoring, modelling, prediction and analysis tools to aquaculture farms has potential to improve operations and alleviate key challenges facing the industry. Fish feed represents 50-70% of fish farmers' production costs while the growth rate of fish is intrinsically linked to feed composition and time of supply; precise management can link fish growth with optimal feed schedule and composition, that minimises wastage (and subsequent pollution of surrounding waters) and improves productivity. Disease and parasite-induced impacts is a major issue for aquaculture farms costing the industry up to $10 billion annually and having severe socio-economic impacts. Further parasite-control treatment in salmon farms constitute 7.5% of total production costs [2]. Farming in the open ocean requires ability to respond to natural fluctuations that impact operations, such as dissolved oxygen (DO) concentrations or temperatures, both of which act as stressors, impact feeding and parasitic rates, and even cause mortalities. Today, management of most of these tasks is conducted manually relying on direct human observation or human-centric data acquisition means to observe conditions, combined with decision making based on subjective experience. However, as real-time sensor technologies become more prevalent on farms, the foundation exists to transition the industry from ad-hoc decision making based on heuristics and intuition, to real-time informed decisions backed by AI insights and IoT connectivity.

This article describes a precision fish farming framework we have implemented on farms in Canada, which is also rapidly being implemented in Europe. It is part of an on-going effort to develop a prototype, open-standards-based ecosystem that combines monitoring, modelling, insight and decision towards an autonomous framework to manage farms. It represents a multi-disciplinary collaboration with partners from the aquaculture industry, academia and technology.

II. What is Precision Aquaculture

The rapid development of aquaculture in recent years has been likened to a 'Blue Revolution' [3] that matches the 'Grain Revolution' of higher cereal yields from the 1950s onwards. The industry's rapid growth and expansion globally, however, has caused concerns about negative environmental impacts, such as eutrophication of nearby waters and, habitat alteration. In Europe, annual growth of aquaculture has declined to 1%, partly because of market factors, but also because the industry is subject to stringent regulation regarding sustainable development. These factors have led to a strong focus on the ecological development of aquaculture in marine systems, and the promotion of terms such as "ecological aquaculture" and "ecoaquaculture". Coupled with the need for greater efficiencies and economies of scale to empower the sustainable growth of the industry, precision aquaculture focuses on exploiting modern technologies towards the ***eco-intensification*** of aquaculture farms.

Data generated on modern aquaculture farms extend across a wide variety of forms. In situ sensors sample large numbers of environmental variables such as temperature, current velocity, dissolved oxygen (DO), chlorophyll and salinity. Remotely-sensed environmental data can sample much larger spatial domains and can be at the bay-scale – from land-based sensors such as CODAR-type HF radar – or at the global scale from satellite-based monitoring system. Informing on farm operations also requires sampling of animal variables such as size, clustering behaviour, and movement, and this is typically done using underwater technologies such as video monitoring, hydroacoustic technology and aerial drone imagery.

Further, there are large datasets of pertinent variables that are generated by numerical models such as weather or ocean circulation products. These datasets constitute huge data volumes with distinct characteristics. Integrating and extracting information from these disparate data sources are key to encapsulating the full dynamics of the farm environment and enabling effective management. Related data from mathematical models are estimates of fish growth and behaviour that can be used to guide expected conditions and decision [4].

The overarching aims of precision aquaculture have been defined as [1]: 1) improve accuracy, precision and repeatability in farming operations; 2) facilitate more autonomous and continuous biomass/animal monitoring; 3) provide more reliable decision support and; 4) reduce dependencies on manual labour and subjective assessments thus improving staff safety. Similar to precision *livestock* farming [5], precision *fish* farming has been decomposed into three conditions that must be fulfilled. We note that in addition to these caveats, we include sensing of the ambient environment (e.g. water temperature, oxygen), a consideration that is less important in agriculture where animals can be housed. The basic requirements of precision aquaculture are:

A. Continuous monitoring of animal variables (i.e. parameters related to the behavioural or physiological state of the fish),

B. a reliable model to predict how animal variables dynamically vary in response to external factors, and,

C. observations and predictions integrated into an on-line system for decision or control.

Achieving these objectives is dependent on the successful implementation of a range of innovative technologies related to sensors, computer vision and AI, enabled by a readily inter-connected edge, fog and cloud ecosystem. Central to this paradigm shift from human to autonomous management is an IoT platform to link information from different components, understand current status against desired or model-predicted benchmark, and return insight from data in terms of actionable information, such as modified feeding protocol or defined health intervention or treatment.

Conceptually, the cultivation of fish in the ocean has parallels with terrestrial livestock farming. In practise, however, livestock farming is more amenable towards direct human and interaction contact than is possible in the marine-based counterpart. Modern fish farms are comprised of cages with up to 200,000 fish. As farms are typically composed of 10 – 20 cages, and multiple farms are often co-located in a bay, the total number of individual fish is enormous. This precludes the direct translation of concepts from livestock farming, and in practise, precision aquaculture is a marriage of approaches developed for both precision livestock *and* grain cultivation, i.e. fish are not managed as individuals as are cows, yet are obviously more complex in management than plants.

III. DeepSense for Aquaculture

DeepSense[1] is a big ocean data innovation environment, powered by IBM, that brings together academia and industry to drive growth in the ocean economy. A key component is the commercialisation of IoT technologies towards better management of fish farms. Specifically, a new research program involving Dalhousie University, DeepSense, InnovaSea, Cooke Aquaculture, and IBM has been created to research sensor networks, big data, and analytics applied to fish farming in eastern Canada. Dalhousie University in Halifax, Nova Scotia is a global leader in the marine sciences and aquaculture, and home of DeepSense in the Faculty of Computer Science. The university collaborates with InnovaSea also headquartered in Nova Scotia. Cooke Aquaculture is an international seafood company originating in New Brunswick, Canada with a deep

[1] http://www.deepsense.ca

commitment to innovation and sustainability, cooperating closely in research with Dalhousie. The unique combination of industry, technology and scientific expertise further positions Nova Scotia as a global centre of ocean technology, developing innovative solutions to empower aquaculture operations.

A. *Farm monitoring*

Within this precision fish farming initiative, hundreds of real-time underwater wireless acoustic sensors have been deployed in Canada at multiple fish farms by Cooke and InnovaSea2. Sensors take 100,000 measurements daily, analysing 11 million data points about temperature and tilt, salinity, dissolved oxygen, blue-green algae, chlorophyll and turbidity. Fig. 1 presents a schematic of the sensor deployment that collects pertinent environmental variables within a cage. Additional data on fish position are provided by the "CageEye" acoustic system3, as well as individually acoustically tagged fish.

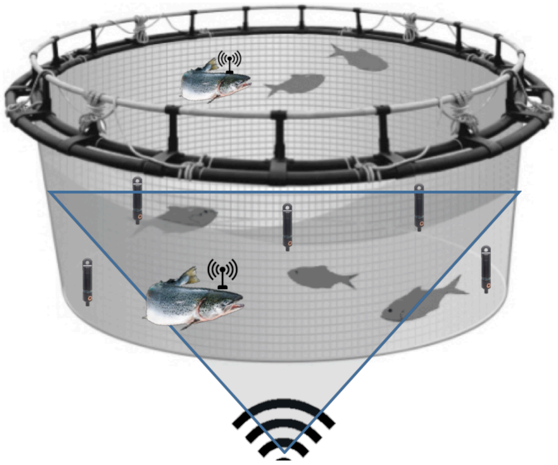

Fig. 1 Sensor configuration within a stylized cage. Nine sensors were deployed within each cage (we only show five to illustrate approximate locations) consisting of four sensors at 2m depth in each corner (north, south, east and west), four sensors at 8m depth in each corner, and one sensor at 4m depth in the centre of the cage. This sensor density is for research purposes of understanding spatial variation in the net pen. Operational metrics related to fish position and behaviour are estimated using acoustic systems such as "CageEye" system as well as a number of individually tagged fish.

All data generated on farms are communicated to IBM® Cloud[4], utilising the open-standard MQTT Protocol for data transport. For each cage, a comprehensive set of variables are collected, communicated and updated, continuously informing on environmental and animal conditions.

The ocean consists of complex environmental conditions (tides, winds, water masses, ice), that impact farm operations, safety and health of the fish. Hence, information *external* to the cage are pertinent to operations and management. Satellite measured observations, weather data and numerical models of the ocean all generate information impacting at the farm-scale. Real-time analysis and decision require the ability to rapidly query and extract pertinent variables from these datasets. We integrate in-situ and geospatial datasets using a big data platform, PAIRS (Physical Analytics Integrated Repository and Services) [6] – a service that processes petabytes of data and addresses the spatial and temporal complexity associated with heterogeneous data integration. Built on top of the open source big data technologies Hadoop and HBase, PAIRS aims to accelerate data queries by curating and storing geospatial datasets from diverse sources (e.g. NOAA, NASA, ECMWF, etc.) in a scalable storage table that can be rapidly accessed and retrieved.

B. *Modelling within precision aquaculture*

The objective of precision aquaculture is to manage the observed status of the farms relative to a defined benchmark (e.g. projected biomass). Hence a key functionality of the IoT platform is the capability to manage various machine-learning models and integrate with the different data streams coming from sensors, weather data, and other open sources. A range of machine learning and mechanistic models relate to managing aquaculture operations. In particular, we focus on:

- Mechanistic and data-driven models to predict fish health, biomass, and mortality based on information on feed and environmental stressors
- Predictive models to inform on outbreaks of parasitic infections
- Deep learning models to forecast oceanographic condition multiple days/weeks in advance

Fish feed is the most expensive part of aquaculture and causes environmental problems when excess product sinks to the bottom. Optimal supply of feed is a complex selection that includes feed composition, growth stage, biomarkers and environmental conditions. While mechanistic models have been developed that simulate growth rates based on feeding regime and environmental conditions, the nonlinear relationships and sensitivity to external events such as diseases or parasites, have made prediction difficult [7].

A practical solution requires that prediction be based on observed status to maintain accuracy. One approach combines mechanistic models with observations using data assimilation – a mathematical technique that incorporates process knowledge encapsulated in a physics-based model with information from observations describing the current state of the system (described schematically in Fig. 2). A precision aquaculture implementation can be summarised as:

- dynamic process models for individual fish growth based on feeding regime and environmental conditions are implemented
- continuous update of model state based on actual fish position and/or biomass as measured by the CageEye system described in section A or the Biosonics aquaculture biomass monitor[5].

[2] http://www.rtaqua.com
[3] http://www.cageeye.no
4 https://www.ibm.com/cloud

[5] https://www.biosonicsinc.com/products/aquaculture-biomass-monitor/

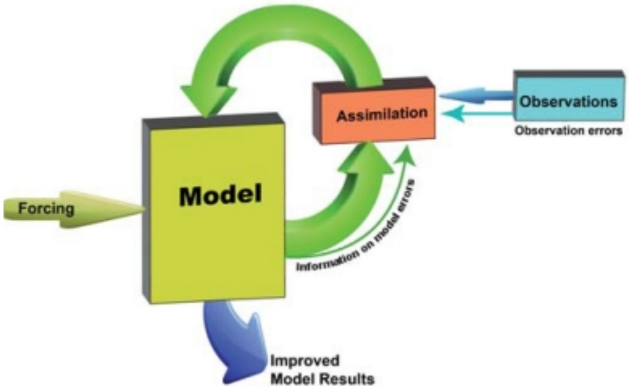

Fig. 2: Mechanistic models contain errors that increase with time due to model imperfections and deviations of forcing conditions from reality. Data assimilation minimizes these errors by correcting the model stats using new observations (from: *[10]*)

Within the former approach, data assimilation concepts have seen enormous application since the 1960s as scientists aimed to update models using *sparse* sensor observations [8]. As sensors become more prevalent, data-intensive computing is continuing to transform industries and decision [9]. Leveraging the large datasets being generated on aquaculture farms has multiple advantages, particularly related to extracting insight from highly complex nonlinear processes not amenable to encoding within a set of explanatory equations. An obvious case in aquaculture is fish health and in particular parasitic outbreaks.

Sea lice presence in salmon farms is a complex interplay of hydrodynamics, lice load, temperature, and position of the fish in the water column. Nonlinear, opaque relationships have traditionally made mechanistic modelling impractical. More recently, IBM, in collaboration with industry stakeholders, has implemented a deep learning model that collates data from multiple sources and predicts sea-lice outbreaks, termed "AquaCloud". The model was fed with data on environmental conditions and lice counts from over 2,000 salmon cages along the Norwegian coast. Combining a dense network of environmental sensors and manual sampling (of lice count), the deep learning model provide two-week-ahead prediction of lice count with 70% accuracy [11]. Within a precision aquaculture framework, advance prediction of parasitic outbreaks present opportunities for improved management and treatment that can reduce severity of outbreak and the invasiveness of treatment.

Machine learning-based models for geophysical processes is an active area of research. The authors recently developed and demonstrated a machine-learning surrogate model for a physics-based ocean-wave model [12] The machine-learning model yielded enormous speedup (> five-thousand-fold) in computational time while maintaining accuracy that was well within the confidence bounds of the physics-based model. In effect, deep-learning based approaches enable the transition of complex modelling systems from HPC to edge devices (naturally the training of the models is expensive, but once trained, deployment is cheap). This approach is being extended as part of DeepSense with data from hundreds of sensors being fed to deep learning models that provide continuous prediction of oceanographic variables multiple days in advance. A number of studies have produced promising results using machine-learning to predict pertinent variables such as ocean temperature [13], and algal blooms [14].

C. *From data to decision*

The key objective of precision aquaculture is moving beyond data – towards decision. As part of the DeepSense platform, an IoT network has been developed to integrate data from hundreds of sensors at salmon cages in Canada. This is complemented by a model-management framework that enables tracking of models and functionalities, automatic subscription to data streams and relationships between different models (geospatial, vertical dependencies, etc.). Efforts are ongoing to integrate this with an evidence-based decision platform. Currently, we focus on two key challenges facing fish farms:

1. Optimising feeding to maximise productivity and minimise environmental impacts
2. Inform on health intervention practises to mitigate sea-lice

Optimising fish feed needs to consider the composition and schedule in response to external conditions. The objective is the supply of nutritionally-appropriate feed at a rate and frequency that maximises uptake by the fish. Some guidelines may instruct – such as not to feed when environmental stressors may impact consumption – but ultimately real-time conditions and behaviour need to inform decision.

The rate of supply of feed can be related to the monitoring of cage biomass and activity. Namely, when monitoring activity indicates that feeding behaviour has concluded (i.e. the fish move away from the surface where feed is supplied), then feeding is stopped to prevent wastage and environmental pollution. This is implemented via an AI system that processes information from video or the acoustic monitoring sensor to label observed data as "feeding" or "not feeding".

As with terrestrial farming, there is extensive knowledge on the most appropriate feed composition at different stages of the fish growth, health and seasonal cycle. A key challenge is applying this knowledge to real-world scenarios in the face of uncertainty. An IoT solution provides a continuous update of measured fish size against predicted values enabling response to deviations. Namely, an online AI system monitors current biomass and recommends most appropriate feed composition based on a database of growth conditions and nutrient requirements.

Parasite and pathogen outbreaks have traumatic impact on farms, leading to mass mortalities, causing fish to be unmarketable, and generating huge damage to the public perception. As is often the case, prevention is preferable to a costly cure that is dependent on harsh chemicals or highly invasive mechanical removal. Predictive models, as described in section B, allow for advanced treatment to avoid these symptoms reducing fish loss and economic losses.

Fig. 3 presents a schematic of the different components of a precision aquaculture framework. It can be broadly decomposed into four pillars: the monitoring of environmental and operational conditions at the cage- farm- bay- and ocean-scale (considering both in situ generated data and existing data from sources such as NASA Modis or ECMWF); integration of data

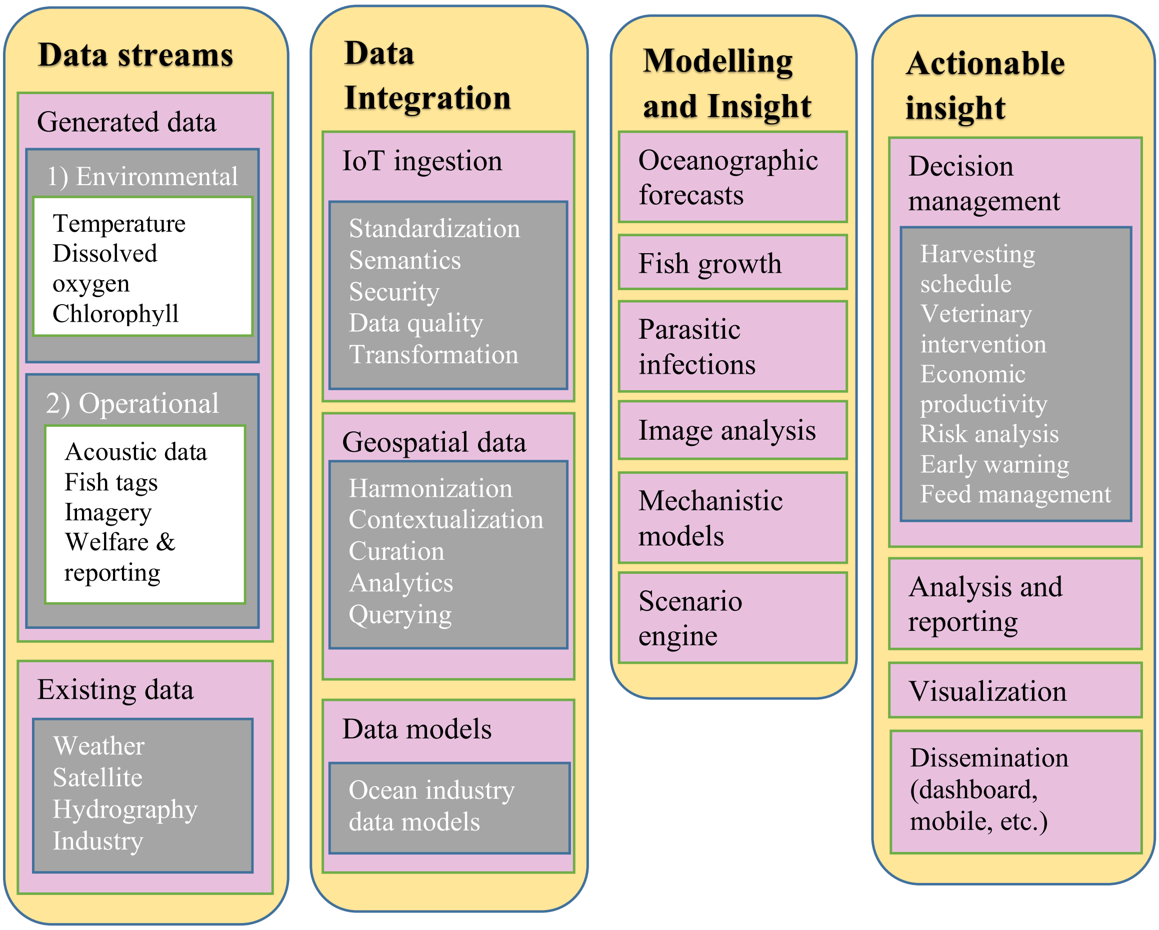

Fig. 3: Schematic of the precision aquaculture framework encompassing: the in-situ monitoring of farm conditions and operations, integration of the generated and existing data in a unified cloud platform, analytics and machine learning applied to the data to generate insight, and the dissemination of that data to stakeholders in an actionable format

from available sources into an accessible form; applying models and analytics on the data to generate insight; and the dissemination of that insight to stakeholders in an actionable format (directly to farm operators, summary metrics to management, report generation for regulatory requirements, etc.).

IV. The Future of Precision Aquaculture

Fish farming is a relatively young industry but, in some ways, has been quicker to adapt to difficult circumstances than land-based farming because of modern technology. The next phase of industrialisation is dependent on using data to inform decision. Certain challenges exist related to its location in the ocean – requiring robust, low-cost sensors capable of underwater and in-air wireless connectivity. However, the industry has seen huge progress from this regard with many farms being equipped with a dense network of sensors streaming data in real-time. Similar to other industries, the current focus is extracting actionable insight from IoT data [15].

Interoperability poses a significant challenge as sensors currently cover a wide range of types, suppliers and levels of sophistication. This extends from legacy sensors storing data in on-board data loggers, to modern sensor stacks reporting in proprietary format to dedicated cloud platforms. DeepSense is committed to an open-standards approach based on MQTT protocol. Extensive work is ongoing with sensor manufacturers as well as the aquaculture industry more broadly to standardise messaging protocols. These include activities we are developing as part of Horizon 2020 project GAIN (Green Aquaculture INtensification[6]) and previous work conducted by IBM with seven different Norwegian aquaculture companies as part of the AquaCloud project for sea lice data. Security and sovereignty of data is critical to fully exploit AI capabilities in an ethical and commercially sustainable way. An often-overlooked part is the content returning from sensors and empowering analytics to understand and process these messages. Interoperability of these messages with agnostic IoT platforms requires insight into what

[6] https://www.unive.it/gainh2020_eu

the value or content of each sensor refers to via semantic domain models for example [16].

Computer vision is currently receiving a lot of attention at the academic and venture capital level. Proponents claim that computer vision and AI can be used to monitor feeding behaviour, fish biomass, detect sea lice and optimise the supply of feed, medicine and other resources to farms [17].

At its core, precision aquaculture is dependent on leveraging IoT technologies to move beyond data towards insight. By integrating data from heterogeneous, disparate sources into a unified cloud platform, it promises to move from heuristics and experience towards evidence and information. Aquaculture is projected to supply 62% of fish for human consumption by 2030 and securing this supply is contingent on eco-intensification of the industry based on data.

V. Conclusion

Because precision fish farming is in the early stages, the development and proliferation of sensors is a growth area. A wide variety of sensors are feasible, including optical, acoustic, and biological sensors for currents, particles, pathogens, and harmful algal blooms. Moreover, a similarly diverse array of image-based data are being applied to fish farming ranging from direct videography of fish to satellite remote sensing. The use of drones in data capture are an obvious application of airborne technology. The attendant development of AI to analyse images and interpret essential information related to fish behaviour and health is an active area of research. While the benefits of these advances to husbandry is apparent, their application to public facing indicators of sustainability is critical. The expansion of big data in fish farming should have spinoffs for a larger conversation regarding indicators of sustainability in aquaculture.

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References

[1] M. Føre *et al.*, "Precision fish farming: A new framework to improve production in aquaculture," *Biosyst. Eng.*, vol. 173, pp. 176–193, Sep. 2018.

[2] A. P. Shinn, J. Pratoomyot, J. E. Bron, G. Paladini, E. E. Brooker, and A. J. Brooker, "Economic costs of protistan and metazoan parasites to global mariculture," *Parasitology*, vol. 142, no. 1, pp. 196–270, Jan. 2015.

[3] B. A. Costa-Pierce, *Ecological aquaculture : the evolution of the blue revolution*. John Wiley & Sons, 2008, 2002.

[4] M. Føre *et al.*, "Precision fish farming: A new framework to improve production in aquaculture," *Biosyst. Eng.*, vol. 173, pp. 176–193, Sep. 2018.

[5] D. Berckmans, "Automatic on-line monitoring of animals by precision livestock farming," in *Livestock production and society*, R. Geers and F. Madec, Eds. Wageningen Academic Publishers, 2006, pp. 27–30.

[6] L. J. Klein *et al.*, "PAIRS: A scalable geo-spatial data analytics platform," in *2015 IEEE International Conference on Big Data (Big Data)*, 2015, pp. 1290–1298.

[7] M. Føre *et al.*, "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*, vol. 464, pp. 268–278, Nov. 2016.

[8] M. J. Martin *et al.*, "Status and future of data assimilation in operational oceanography," *J. Oper. Oceanogr.*, vol. 8, no. sup1, pp. s28–s48, Apr. 2015.

[9] A. Hey, S. Tansley, and K. Tolle, *The fourth paradigm: data-intensive scientific discovery*. Seattle, USA: Microsoft Research, 2009.

[10] P. Houser, "Improved Disaster Management Using Data Assimilation," in *Approaches to Disaster Management-Examining the Implications of Hazards, Emergencies and Disasters*, IntechOpen, 2013.

[11] T. Hoel, "Data science helps Norway's fish farmers keep salmon populations healthy." [Online]. Available: https://www.ibm.com/blogs/cloud-computing/2018/09/17/data-science-norway-fish-farmers/. [Accessed: 14-May-2019].

[12] S. C. James, Y. Zhang, and F. O'Donncha, "A machine learning framework to forecast wave conditions," *Coast. Eng.*, vol. 137, 2018.

[13] S. Wolff, F. O'Donncha, and B. Chen, "Statistical and machine learning ensemble modelling to forecast sea surface temperature," Sep. 2019.

[14] F. O'Donncha and S. C. James, "A machine-learning-based approach to forecast harmful algal blooms," in *Aquaculture Europe*, 2019.

[15] "IDC European Vertical Markets Survey," 2017.

[16] J. Ploennigs, J. Cohn, and A. Stanford-Clark, "The Future of IoT," *IEEE Internet Things Mag.*, vol. 1, no. 1, pp. 28–33, 2018.

[17] M. J. Coren, "Aquaculture is the latest hotness for Silicon Valley venture capitalists in 2018 — Quartz." [Online]. Available: https://qz.com/1256208/aquaculture-is-the-latest-hotness-for-silicon-valley-venture-capitalists-in-2018/. [Accessed: 14-May-2019].

BIOGRAPHIES

Dr. Fearghal O'Donncha is a Research Scientist at IBM Research – Ireland. His work focuses on applying simulation models, analytics and machine learning techniques to assist industry operations. This encompasses developing and deploying simulation-based models, integrating sensor data from a variety of IoT platforms, developing AI based models that extract value from sensor or expert data, and optimising these tools to a variety of HPC and Cloud based platforms. Fearghal is an adjunct faculty member at the National University of Ireland, Galway (NUIG).

Jon Grant is a Professor of Oceanography at Dalhousie University. He is the NSERC-Cooke Industrial Research Chair in Sustainable Aquaculture, in a multi-year partnership with Cooke Aquaculture, one of the major global aquaculture and fisheries companies. Trained as a benthic ecologist, he has a BSc from Duke University and PhD from the University of South Carolina. Jon has worked in aquaculture-environment interactions for 30 years and is co-editor of a new book entitled 'Goods and services of marine bivalves