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Validating non-invasive growth measurements on individual Atlantic salmon in sea cages using diode frames

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ABSTRACT

Most Atlantic salmon production takes place in large sea cages where there are limited opportunities to record growth on individual fish. This limits management capabilities for monitoring mean weight and thus total biomass, pellet sizes, feed volumes and the estimation of time until harvest. Furthermore, cause and effect of perturbations and arrested growth cannot be established or interceded on and genetic selection is limited to stocking and harvest measurements. The fusion of passive integrated transponder (PIT) identification and diode frames offers the possibility to noninvasively monitor the growth on thousands of individual fish. However, the accuracy of diode frame measurements for population- and individual level growth and biomass estimation has not been assessed. We stocked over 5000 individually PIT tagged Atlantic salmon post smolts in a net-cage in the sea and monitored growth using a diode frame and PIT tag reader. At the end of the growth period all fish were measured for body length and weight using the intensive gold standard methods of manual recording. At the population level diode frames were highly accurate with a mean difference of 0.002% for length and 4% for weight. Individual level length and weight records were repeatable 0.34 and 0.35, respectively. A single measurement at individual level from diode frames were moderately concordant with the gold standard measures (concordance correlation coefficient (CCC) of 0.52 for length and 0.57 for weight). By exploiting the repeatability and high throughput of diode frame measurements it was possible to increase the number of records per fish to a maximum of 5 resulting in CCC of up to 0.88 for length and 0.81 for weight. Diode frame measurements may hold promise for continuous growth measurements at sea needed in genetic evaluations.

1. Introduction

The Atlantic salmon (*Salmo salar*) aquaculture industry has undergone significant intensification and expansion since its inception in the 1970s, reaching a current global production of 2248 thousand tonnes in 2016 (FAO, 2018). Most Atlantic salmon production in countries like Norway, Scotland, Chile and Canada takes place in sea net-cages. In recent years, the production trends have seen increasing net-cage sizes and capacities reaching (60,000–130,000 m^3) and up to 200,000 fish per cage (Føre et al., 2018a, 2018b). In Norway, expanding operations is strictly regulated to a limited number of licenses, a maximum allowed standing biomass per licence (780 tonnes) as well as a maximum biomass density (25 kg/m^3) per cage. Therefore, increasing profitability and sustainability requires improving the production efficiency of the existing farms. Research into individualised fish response to management interventions, feed intake, growth and causes for arrested growth as well as genetic improvement have gained interest (Føre et al., 2018a, 2018b). However, direct human observation of fish under these conditions is insufficient for decision support and on-line monitoring of physiological, behavioural and welfare of individual fish (Føre et al., 2018a, 2018b). A continuous on-line and non-invasive method of recording response variables of individual fish *in situ* could overcome the limitations of direct human observation and measurement.

One of the most economically important sources of information for daily management of Atlantic salmon in sea cages is accurate and precise biomass and body size distribution of fish (Lines et al., 2001). This information allows adjusting feeding amounts and sizes of pelleted feed to ensure optimal feed conversion efficiency and save cost through

Abbreviations: AGD, amoebic gill disease; CV, coefficient of variation; CCC, Lin's concordance correlation coefficient; FAO, food agricultural organisation; HPT, high performance transponder; LiDar, Light Detection and Ranging; N, number of fish; PIT, tag – passive integrated transponder tag; R, Pearson's correlation coefficient; R^2, coefficient of determination; RFID, radio frequency identification; SD, standard deviation

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prevention of feed losses into the surrounding environment (Saberioon et al., 2017). Furthermore, accurate body size and biomass density information allows maintaining total biomass and stocking densities within legal limits, and provides the potential to detect underlying causes of arrested growth and monitoring needed to ensure fish welfare. Lastly, accurate body size information allows planning and preparations for slaughter and sale (Beddow et al. 1996; Folkedal et al., 2012; Aunsmo et al., 2013). Traditional methods for biomass estimation require knowledge of the number and average weight of smolt put into the sea cage, growth, mortalities, amounts fed and water temperature (e.g. Nordgarden et al., 2003). The predicted growth curves cannot account for numerous and variable environmental factors experienced in sea cages and therefore accuracy decreases, and uncertainty increases during the course of production (Zion, 2012). Periodically sampling fish and manually measuring length and weight can be used to update growth curves, however this approach is time consuming, may stress or damage stock and typically results in biased estimations. For example, Ross et al., (1998) estimated that hand nett samples have a difference in accuracy ranging from 1 to 12% between samples and 15–25% between samples and the entire measured population. In other words, a non-invasive, continuous and high throughput method of accurately recording fish size in sea cages is essential for improving the economic and welfare management needed for more sustainable Atlantic salmon production at the grow-out farms.

Another method for improving production efficiency is genetic selection as genetic gain is both cumulative and permanent (Falconer and Mackay, 1996). Genetic selection for growth has been largely successful in Atlantic salmon with a 200% cumulative gain in harvest weight reported over 10 generations (Janssen et al., 2017). However, selection information is typically limited to body size measured at entry into sea cages and at harvest (Janssen et al., 2017). Increased frequency of recording of body size of fish throughout their time in sea cages offers the possibility to increase the rate of genetic gain by increasing the accuracy of selection through repeated measurements (Rutten et al., 2005). In addition, it also gives the possibility to infer and select for health status based on observed growth rates through the use of multi-trait mixture models (Lillehammer et al., 2013). However, a perquisite of genetic improvement is the ability to distinguish or identify the individuals which are being measured.

Technological advances have led to two categories of systems which can continuously and non-invasively record morphological features of fish underwater (such as length and width) from which their body weight can be predicted. The first is computer vision based approaches such as stereoscopic cameras, acoustic cameras and LiDar, which have generated considerable research interest in recent years (Saberioon et al., 2017). Of these, stereoscopic cameras which consist of two adjacent cameras and trigonometric functions to estimate linear measurements, have been tested in Atlantic salmon (Beddow et al., 1996) and Atlantic bluefin tuna (Shieh and Petrell, 1998; Puig-Pons et al., 2019) in sea cages. The biggest challenges faced by computer vision technologies are the highly spatial and temporal variations in the rearing environment (lighting, salinity, visibility etc.) and the fish under measurement (distances, motion, orientation and density) which has limited development in commercial applications. The second category is diode frames, in which a frame consisting of a double rectangular planer matrix of infrared light beams, is suspended within the water column (Folkedal et al., 2012; Gudjonsson and Gudmundson, 1994). As fish swim through the frame and obstruct the infrared light curtain, infrared sensors map the shadow and velocity of the fish through the frame and can reconstruct a 3D representation (Ruff et al., 1995). A disadvantage of diode frame is that the weight is predicted from empirical body measurements such as length, but the prediction model is not publicly available and out of the user's control. In addition, representativeness of the samples can be called into question as some fish are reluctant to swim through the frame and Atlantic salmon display size dependent swimming depths which are not captured if the frame is maintained at a fixed depth (Folkedal et al., 2012; Zion, 2012). Problems associated with sample representativeness and frame location can in principle be overcome with individual identification of fish which pass through the frame. Passive integrated transponders (PIT) tags are routinely used to identify individual fish in experimental trials or breeding programmes. Sensor fusion of PIT tags and diode frames thus offers the possibility to continuously record the size of individual Atlantic salmon in sea cages.

As the repeatability and individual level accuracy are relevant for breeding purposes and the population level accuracy is relevant for rearing purposes, the objectives of this study are as follows: To evaluate the repeatability of continuous measurements of length and weight in Atlantic salmon in sea net-cages. Secondly, assess the population level accuracy (mean difference between diode and manual recording in percent of the mean of the manual measurement in percentage) and variability of diode frame measurements of body length and weight against manual recordings. Lastly, assess the individual level accuracy (difference between diode and manual recording in percent of the manual measurement) and concordance of diode frames and PIT tag reader fusion for body length and weight against manual recordings.

2. Materials and methods

2.1. Design and fish

In April 2018 approximately 5500 Atlantic salmon individually tagged with passive integrated transponders (PIT-tags) (HPT12 12 mm, Biomark Ltd, Boise, USA, www.biomark.com) were smoltified at MOWI's Øyerhamn facilities (60.1°N, 0059°E) (MOWI ASA, Øyerhamn, Norway). Upon reaching a weight of 157.9 ± 40.2 (mean ± SD) grams the fish were transported and transferred to a sea cage (12 × 12 × 12 m Dimensions) at Austevoll Research Station (60°N, 0053°E) of the Institute of Marine Research on 03 May 2018. On 25 May 2018, 400 (7%) Ballan wrasse *Labrus bergylta* were added to the cage to keep salmon lice at low levels.

The fish were fed a commercial feed from Skretting AS; during the first weeks Spirit Supreme Plus was used (approximately 45% protein 25% fat, 23 MJ/kg) and with a gradual increasing fat and decreasing protein content over time, while during the last weeks Premium was used (approximately 34% protein, 37% fat and 26 MJ/kg). Monitoring of salmon lice and amoebic gill disease (AGD) was done based on a weekly random sample of 20 fish.

2.2. Continuous growth measurement and individual identification

After an initial acclimation period of two weeks, a diode frame (Biomass Daily, Vaki AS, Iceland, www.vaki.is) (0.6 m × 0.6 m × 0.2 m) with a Biomark 24 V Antenna (Biomark Inc., Boise, USA, https://www.biomark.com/) was installed in the sea cage. The frame was positioned in the mid-radial horizontal plane, approximately 0.5 m from the net wall and periodically repositioned within the cage to best capture recording on the fish. At each repositioning, depth and water temperature was recorded and ranged between 2.5–7 m and 8–17 °C during the trial. As individual fish swim through the frame a time stamped registration is made on it's body length and weight in the Biomass Daily software (Pentair Aquatic Ecosystems, Pentair ASA, Iceland, https://pentairaes.com/) and the time stamped PIT tag identification numbers is registered by the Biomark PIT tag reader (Biomark Inc., Boise, USA, https://www.biomark.com/). Data streams were monitored weekly and interruptions due to hardware and software failures, as well as hardware cleaning and maintenance and management interventions for monitor lice count, amoebic gill-score and 'true' manual recording of reference data (PIT tag, body length and weight) for small samples of the fish were recorded. The measurement period was conducted from (14th May 2018 until 15th October 2018) at which point the fish had reached a mean weight of approximately 2 kgs.

2.3. Manual recording of growth individual identification and meta data

Weekly samples of approximately 20 fish were captured and identified using the PIT tag reader and used to count lice, gill score for amoebic gill disease and estimate tag loss for unreadable fish. Dead fish were captured in a sample box over the entire 130-day period and recorded for length, weight, sex and where possible cause of death such as mechanical damage, bacterial infection, emaciation etc. Dead fish information was used to adjust total numbers and biomass estimation for daily management purposes.

A sample of 21 and 100 fish were drawn on day 20 (4 June) and 107 (30 August), respectively, and manually recorded for their PIT tag, length and weight before being returned to the cage. All remaining 5133 Atlantic salmon were anesthetised and identified by PIT tag, then manually recorded for weight and length as the 'gold standard' true value reference data for comparisons with diode frame data over three days 154–156 (16th −18th October).

2.4. Statistical analysis

2.4.1. Time series fusion and data editing

The optocoupler linking the PIT tag reader time series with the diode frame failed at the start of the trial. In order to account for the fixed and variable time shifts inherent in digital clock time stamping between two or more sensors (Ridoux and Veitch, 2007) we made use of the sensor time series alignment algorithm of Difford et al. (2016) (Supplementary material). The PIT tag reader read 723,986 fish identification numbers and the diode frame read 312,440 fish over the 153 day period. The numerical discrepancy is likely due to an internal filtering algorithm in the diode frame which deletes all observations where the entering velocity differs from the exit velocity of fish (Haugholt et al., 2016) or possibly multiple PIT tag readings as the fish transitions through the frame.

A near fixed time shift of 2 hr and 4.7 s was detected and validated against the time when the frame was recorded as having been removed from the sea cage for cleaning (see Supplementary Fig. 1). Time aligned continuous length and weight measurements were merged with PIT tag identification numbers, as the tolerance for the sensor time alignment was 2 s, observations within 2 s of each other were removed leading to 35,350 matched merged observations on 4980 fish with high certainty (see Table 1 for sources of data attrition).

2.4.2. Repeatability of continuous length and weight measurements

Continuous growth measures weight and length were analysed using linear mixed models (Eq. (1)) by means of the HPMIXED procedure in SAS (ver. 9.4; SAS Institute Inc., Cary, NC). A Kenward–Roger correction was utilised for computing the correct denominator degrees of freedom of fixed effects in the presence of repeated measures (Kenward and Roger, 1997).

$$y_{ijk} = \mu + \beta_1 Day_i + a_j + e_{ijk} \quad (1)$$

where y_{ijk} is the trait of interest (length), μ is the intercept, β_1 is the a fixed regression coefficient on the ith *Day* of recording (i = 42 levels), a_j is the random effect of the jth animal ~ ND (0,I σ_a^2) where **I** is the identity matric and σ_a^2 the random variation due to animal and e_{ijk} is the random residual term ~ ND (0,Iσ_e^2). For weight the same models as (1) was run with the inclusion of also a fixed regression (β_2) on the quadratic term for *Day*. Marginal and conditional coefficient of determination (R^2) terms were computed for both models following (Nakagawa and Schielzeth, 2013). Repeatability of measurement was calculated as Eq. (2) below:

$$\text{Repeatability (t)} = \frac{\sigma_a^2}{\sigma_a^2 + \sigma_e^2} \quad (2)$$

2.4.3. Population level and individual level comparisons

Weight and length records corresponding to the 24 hr period prior to manual recording on days 20, 107 and 153 were extracted and population level means, variances and descriptive statistics computed for both diode frame and manual recording data (see Table 2). Significance tests were conducted by means of Welch two sample *t*-test for unequal variances.

One full week of records immediately prior to the final manual recording at day 153 of the trial (16 October) event was selected for individual level analysis. Data on individual fish measurements was divided into classes based on increasing number of diode frame records per fish and means calculated per individual. Concordance analysis was conducted across datasets to evaluate the accuracy, variability, correlation between diode frame measurements and manual recording for the entire population.

3. Results and discussion

3.1. Sources of error and attrition

The sources of error and attrition can be found in Table 1 and can largely be summarised into three areas: instrument malfunction, mortalities or tagging error and data filtering. The PIT tag reader and diode frame cumulatively malfunctioned approximately 26% of the time during the trial period. A case study by the diode frame manufacturer reported malfunction between 8% and 36% of the time (Riveros, 2016). Based on the 23 weekly samples of fish drawn during the trial, it is estimated approximately 7% of the fish were either miss tagged, the tag was lost or unreadable. A total of 316 dead fish were recovered during the trial resulting in a mortality rate of 6%. Cumulative mortalities of 6.5–9.0% have been reported by previous studies testing diode frames in Atlantic salmon sea cages (Føre et al., 2016). The PIT tag reader regularly resulted in spurious duplicate readings per fish which were removed, these could be due to a fish remaining in close proximity to the antenna or multiple registrations as the fish passes through the energised antenna field, as is often reported with RFID readers (Mahdin and Abawajy, 2011). The diode frame has an internal data filtering algorithm which removes readings where fish enter and exit the frame at different velocities. We estimate this to account for 33.1% of readings based on the difference between diode frame records and PIT tag records corrected for duplicates and tag loss. The failure of the optocoupler to merge the two different time series necessitated the need for a time alignment algorithm. As the tolerance for this merger was set at 2 s we needed to filter out consecutive observations falling within a ± 2 s sliding window, to ensure that only high confidence match merged identification numbers and records were retained and this resulted in a 61.2% loss of observations. The inability to mark and visually distinguish the passing of individual fish through the frame limits our ability to validate our time alignment algorithm, however we have previously validated this algorithm in livestock where visual validation is feasible (Difford et al., 2016). Furthermore we stocked 3.2 fish per m^3 within the range reported in literature (3–7 fish / m^3) (Folkedal et al., 2012; Føre et al., 2016; Føre et al., 2018a, 2018b), however higher

Table 1
Sources of error and data attrition during recording.

Source	Unit	Total Units	Unit lost	Lost,%
Frame malfunction	Days	153	38	24.8
Tag reader malfunction	Days	153	2	1.3
Tag loss or unreadable	Percentage	100	7.0	7.0
Mortalities	Individuals	5287	316	6.0
Spurious tag duplicates	Observations	760,500	323,462	57.5
Time series fusion	Observations	437,038	270,406	61.2
Frame algorithm	Observations	467,630	155,190	33.1
Final Dataset	Observations	723,986	688,636	95.4

Table 2
Repeatability animal model parameters estimates for identification matched length and weight from diode frames.

Trait	Units	Int	β_1	β_2	σ^2_a	σ^2_e	t	R^2m (%)	R^2con (%)
Length	mm	20.0 ± 0.05	0.215 ± 0.0004	NA	4.35	8.47	0.34	92.4	93.6
Weight	grams	215 ± 7.0	−2.12 ± 0.19	0.093 ± 0.001	23,704	43,367	0.35	91.1	92.5

Int = intercept, β_1 = fixed regression coefficient on days, β_1 = fixed regression coefficient on days squared, σ^2_a = variance explained by individual fish, σ^2_e = residual error variance, t = repeatability, R^2m = R^2 coefficient after accounting for the fixed effects, R^2con = R^2 coefficient after accounting for both the fixed and random effects (see Nakagawa and Schielzeth, 2013).

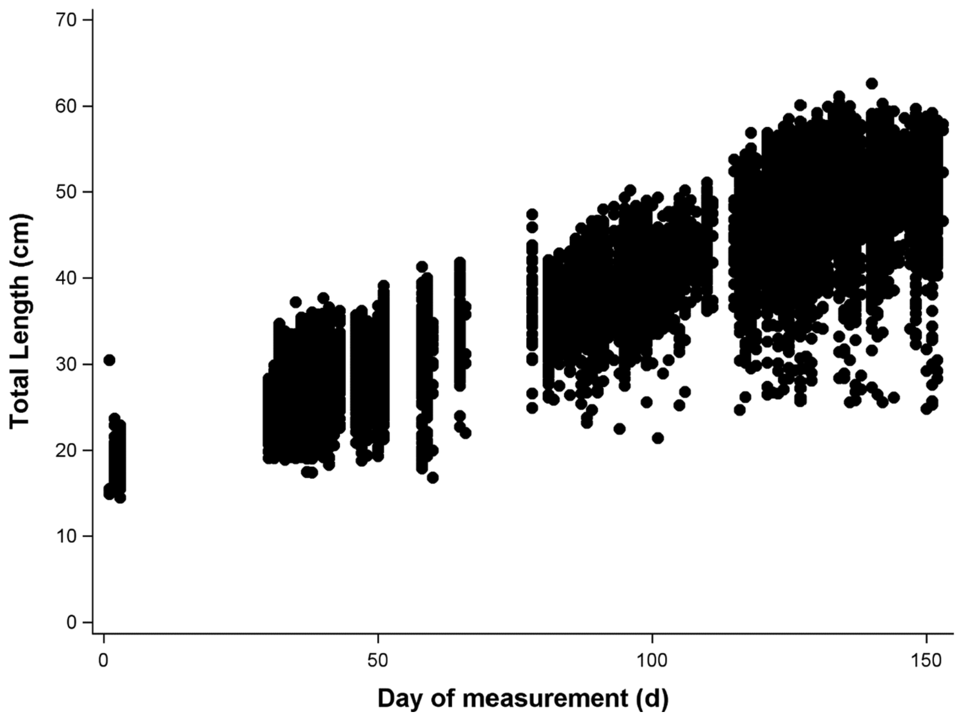

Fig. 1. Diode frame measurements of total body length in cm against day of measurement after match merging.

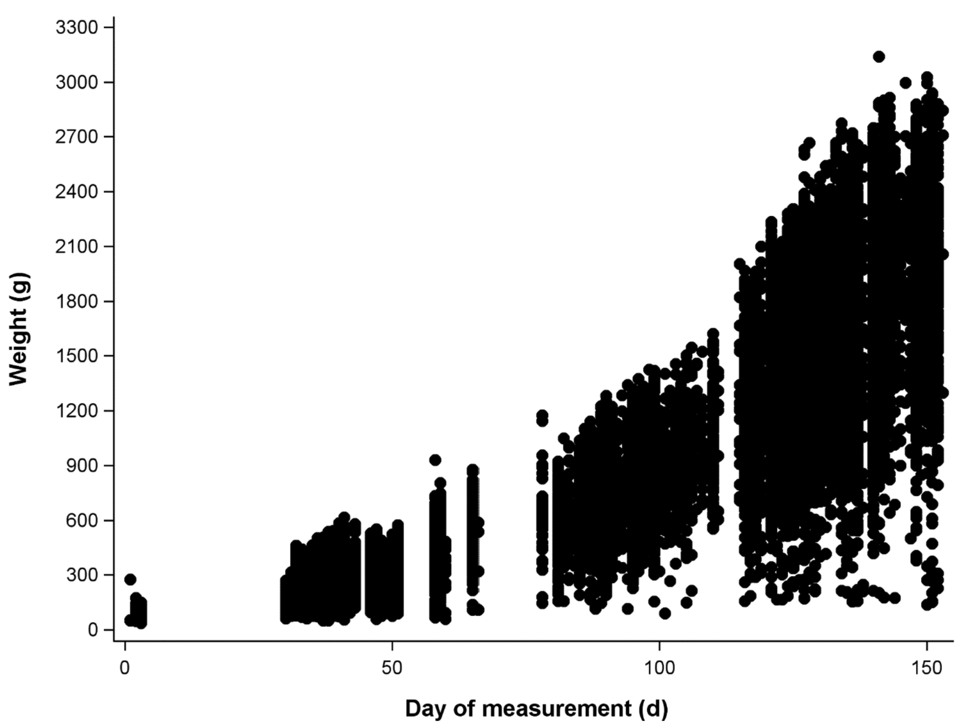

Fig. 2. Diode frame measurements of body weight in grams (g) against day of measurement after match merging.

densities of fish per m^3 in the pen will likely increases traffic through the diode frame and PIT tag reader and could further losses in observations. Despite these sources of error and attrition, a considerable amount of identification matched records remained for further analysis, with a total of 35,350 observations on 4980 uniquely identified fish remained over the experimental period (see Figs. 1 & 2).

3.2. Repeatability of measurements

Length and weight measurements were both significantly repeatable over 153 days at sea 0.34 and 0.35, respectively (Table 2). To the best of our knowledge these are the first reported repeatability estimates for Atlantic salmon at sea, which makes acquiring estimates from literature challenging and highlights the difficulties in recording repeated measurements under this environment. Repeatability estimates have been estimated for body weights in farmed Nile tilapia (*Oreochromis niloticus*) ranging from 0.1 to 0.8 in two separate random regression studies (Rutten et al., 2005; Turra et al., 2012). Similarly for repeatability animal models in farmed rainbow trout (*Oncorhynchus mykiss*) found repeatability of body weights ranging from 0.49 to 0.96 and of body lengths ranging from 0.28 to 0.49 (Hu et al., 2013; Kause et al., 2006). A study estimating repeatability in a natural population of brook trout (*Salvelinus fontinalis*) found length to have a repeatability of 0.29 (Letcher et al., 2011). Gjerde et al., (1994) recorded body weight repeatedly for Atlantic salmon at sea cages over 4 to 27 months at sea. Although they did not estimate repeatability, they did find phenotypic correlations deviating from unity in the range of 0.47–0.95. This would suggest that the repeatability estimates herein are within range of literature, albeit on the lower end of the spectrum of results reported for other species.

The lower repeatability estimate reported herein may be caused by high variability of the measured body length and predicted body weight between measurements close in time due to variation in the orientation and angle at which fish swim through the frame. In which case the residual error or imprecision of measurement is relatively larger for diode frame measurements, and thus results in reduced repeatability estimates (i.e. increased σ_e^2). Conversely increasing the number of replicate measurements (n) per individual and computing means reduces imprecision as a function of $1 + t(n - 1)/n$ (Falconer and Mackay, 1996; Kause et al., 2006). For example, solving this equation to achieve repeatability of 0.50 would require 6 repeated weight records and 9 length records per individual.

3.3. Evaluation of population level accuracy

The population level comparison between diode frame and the gold standard manual recording is presented in Table 3. In general, few studies have evaluated the accuracy of diode frames against the gold standard manual recording. Folkedal et al. (2012) evaluated size stratification over different depths in Atlantic salmon in sea cages using diode frames and compared measurements of weight (n = 19 fish) to the diode frame estimates for the whole cage and found a non-significant −1.9 ± 9.4% difference in their mean weight. We found significant differences between the diode frame and manual recordings at 20 days into the trial, at 18% for length and 33.2% for weight. Although this was a marginally small sample size n = 20 and likely reflects stochastic sampling bias instead of inaccuracy of the diode frame (Ross et al., 1998). Føre et al. (2016) recommended increasing sample sizes to 134–170 per sample, but the accuracy of the diode frame was not the focus of their research and was not reported. When we increased the sample size to 100 fish at 107 days into the trial, the percentage differences in mean length 1.4% and weight 1.7% were greatly reduced and not statistically significant. However, percentage differences in means between methods cannot be regarded as true differences in accuracy, this is because the numerically smaller sample sizes used for the gold standard manual recording may result in sampling bias.

Table 3
Population level comparison between diode frame and manual body length and weight measurements for multiple samplings.

	Diode Frame			Manual recording			
Days	N fish	Mean	CV (%)	N fish	Mean	CV (%)	Difference in Means* (%)
Length (cm)							
20	2954	21.3^a	8.4	21	26^b	15.9	18.1
107	632	42.8^a	10	100	42.2^a	7.4	1.4
153	1530	50.6^a	7.7	5133	50.5^a	7.8	0.002*
Weight (g)							
20	2954	131^a	23.3	21	196.2^b	37.6	33.2
107	632	1028^a	27.5	100	1010.5^a	26.2	1.7
153	1904	1885^a	22.0	5133	1811.0^a	22.6	4.0*

N = number of fish, CV = coefficient of variance, Estimates with different superscripts ^{a,b} differ at $p < 0.05$, * Indicates percentage difference in means between methods.

At 153 days into the trial, we sampled all 5133 fish for manual recording and 1904 (37.1%) of these had passed through the diode frame 24 h before, which allowed us to determine the difference in accuracy between the two methods. For length, the differences in absolute accuracy was less 0.002% and for weight, it was 4%, in both cases not statistically significant. These findings agree with a case study on the manufacturers website which found the differences in accuracy for weight on Atlantic salmon measured in a processing plant after being cultured in sea cages with diode frames, which reported −2.38–1.32% difference in mean in weight (Riveros, 2016). The accuracy of length from this study using diode frames (0.002%) is substantially better than those reported for fish length (2%) in Pacific bluefin tuna using a submersible dual camera system (Costa et al., 2006) and comparable to a stereo vision system (0.02–0.03%) (Torisawa et al., 2011). The absolute accuracy for weight (4%) was comparable to weight estimated from image analysis (3%) (Odone et al., 2001) and a stereo vision on Gilthead seabream in nursery tanks (4%) and sea cages (5%) (Martinez-De Dios et al., 2003). These results demonstrate that the diode frame is highly accurate for length measurements and moderately accurate for weight estimation at the population level. The lower accuracy for body weight is as expected as body weights are predicted from different body size measurement (e.g. length, width, height) of the fish.

3.4. Individual level accuracy

The individual level comparison between diode frame measurements and gold standard manual recording at day 153 into the trial is presented in Table 4. Visual examples of individual level length and weight for three fish using diode frames is presented in Figs. 3 and 4, respectively. For length and weight, there were 1904 fish with at least one diode frame recording within the week prior to manual recording. This comparison differs from that of Table 3, as the samples sizes are standardised across measurement methods in Table 4, i.e. the gold standard measurements are limited to fish with matched measurements using the diode frame (n = 1904). The difference in accuracies was 0.54% for length and 4.5% for weight, both not statistically significantly different from zero ($P > 0.05$). Furthermore, both length and weight from the manual and diode recording were moderately correlated with r = 0.53 and r = 0.58, respectively. As Pearson's correlation coefficient cannot show differences in means (accuracy) or variances (precision), we made use of Lin's concordance correlation coefficient (CCC) to assess overall agreement (Barnhart et al., 2007). Lin's CCC combines all three sources of information and penalises the correlation between two methods if there are differences in means (accuracy) and variances (precision) (Lin, 1989). Concordance of length was moderate (CCC = 0.52) and weight was marginally less concordant

Table 4
Effect of increasing the number of diode frame records per fish on the comparison with manual body length and weight measurements.

Observations per fish	Diode frame			Manual recording				
	N fish	Mean	CV (%)	Mean	CV (%)	Accuracy (%)	r	CCC
Length (cm)								
1	1904	50.6[a]	7.8	50.3[a]	7.8	0.54	0.53	0.52
2	471	50.3[a]	7.4	50.3[a]	7.7	0.06	0.69	0.68
3	142	49.6[a]	7.5	49.6[a]	8.8	0.05	0.83	0.82
4	54	49.4[a]	8.1	49.1[a]	9.1	0.70	0.84	0.83
5	25	48.5[a]	9.8	47.9[a]	11.4	1.21	0.90	0.88
Weight (g)								
1	1904	1885[a]	22.0	1803.7[a]	22.7	4.50	0.58	0.57
2	471	1860[a]	20.8	1801.5[a]	22.3	3.25	0.70	0.69
3	142	1786[a]	20.6	1748.8[a]	23.9	2.12	0.78	0.77
4	54	1751[a]	22.4	1666.1[a]	23.8	5.10	0.78	0.76
5	25	1663[a]	25.9	1550.2[a]	27.0	7.30	0.84	0.81

N = number of fish, CV = coefficient of variation, Accuracy = percentage differences in means, r = Pearson's correlation coefficient, CCC = Lin's concordance correlation coefficient.

(CCC = 0.47) than length. This indicates the diode frame measurements are in closer agreement with the 'true' value for weight and length of the population than the 'true' weight and length of individual fish.

However, both length and weight measurements from diode frames are repeatable (Table 2) and this indicates that the precision can be increased through increasing the number of records per fish (i.e. reducing σ_e^2). For length, taking the average incrementally from individual fish with increasing numbers of diode frame records from 1 to 5 during the week prior to the manual recording, the correlation improved substantially (r = 0.53–0.90) and whilst the differences in accuracy remained stable (0.05–1.21%) and not significantly different ($P > 0.05$) between methods. As a result, the overall agreement between the diode frame and manual recordings increased considerably from CCC = 0.52 to 0.88 for body length and from CCC = 0.57 to 0.81 for body weight.

Considering that the length and weight records were obtained over a 7 day measurement period with the diode frame and that the 'true value' of the fish is changing with time (growth, tail biting, eating etc.) and that manual recording is not free of error (Gutreuter and Krzoska, 1994), CCC is unlikely to reach 1. In a study evaluating camera measurements paired with lasers, reported CCC were in the range of 0.945–0.950 (Rizzo et al., 2017).

For weight, taking the average from individual fish with increasing numbers of records from 1 to 5, the correlation similarly improved (r = 0.58–0.84), however the in-accuracy showed a statistically non-significant tendency to decrease (i.e. the percentage difference in means increased) from 4.5% to 7.5%. As a result, the concordance was lower (0.57–0.81) than the correlation. The diode frame predicts weight based on a linear combination of empirical body measurements generated by the frame such as length, but the prediction model and model fit statistics are not publicly available. However, it is safe to assume that the model predicts weight with some level of error (Gutreuter and Krzoska, 1994) and this is most likely larger than the error on the

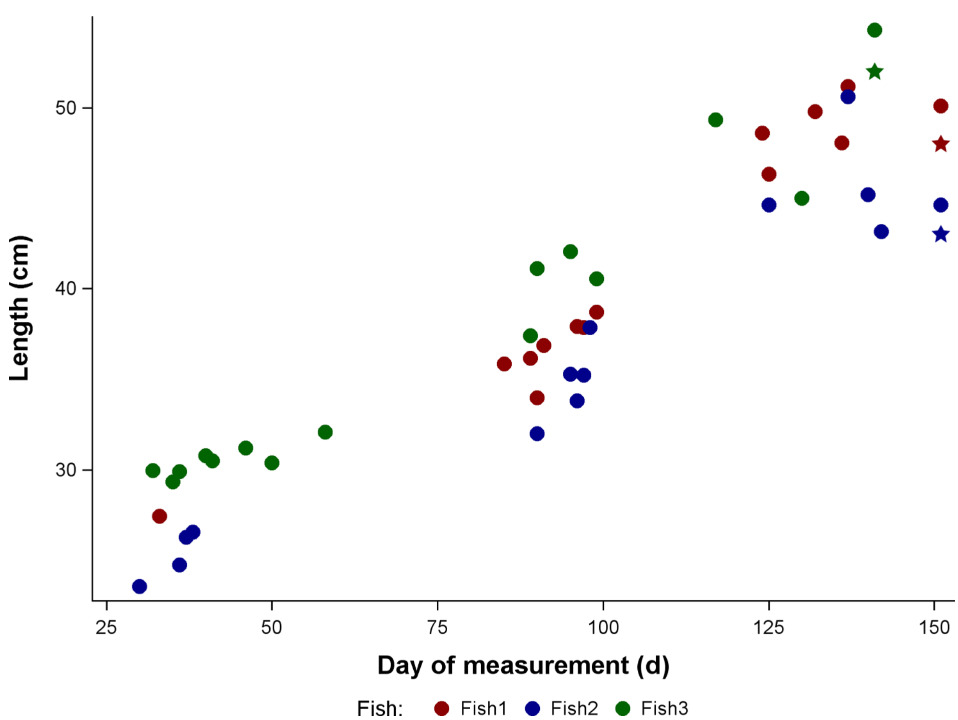

Fig. 3. Diode frame measurements of length in cm against day of measurement (circle) for three example fish and gold standard manual recording at end of trial (star).

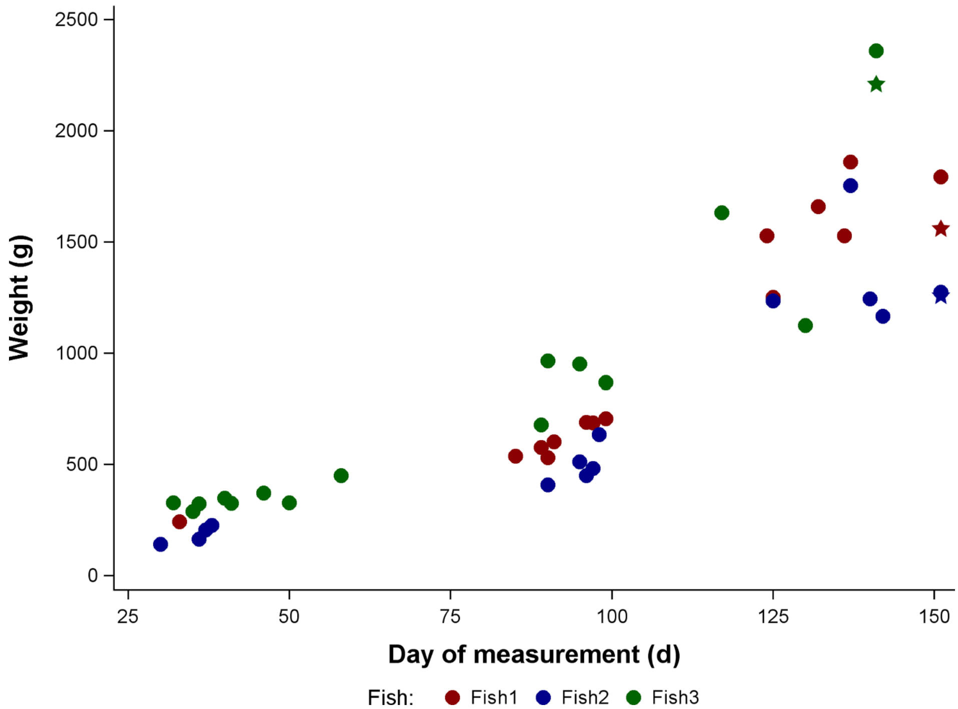

Fig. 4. Diode frame measurements of weight in grams against day of measurement (circle) for three example fish and gold standard manual recording at end of trial (star).

measured length. This is also likely the cause of a lower CCC for weight than for length as the number of records per fish increases.

These findings would suggest that higher concordance at the individual level could be achievable with diode frames for both weight and length, given a better prediction model for weight. However, it is important to note that no fish had more than 5 repeated measurements in the week prior to the manual recordings, so the maximum increase in concordance between the two measurement methods was not reached. Furthermore, a substantial amount of data was, by necessity, removed to ensure only high certainty matched merged fish identification with measurements were retained. Future studies maybe able to achieve greater individual level concordance if these sources of error are circumvented.

3.5. Towards precision fish farming

The core idea of precision fish farming is that measurements of individual fish are suitably accurate to inform quick management decisions to correct arrested growth and improve overall fish welfare (Føre et al., 2018a, 2018b). On the population level the accuracies reported herein for diode frame measurements of weight are suitably accurate for informing biomass based decisions such as harvesting to reduce total allowed biomass on a location or distribution of the biomass on more cages to reduce allowed stocking densities. Furthermore, it is feasible to use diode frame measurements to detect arrested growth on the population as well as full sib family level, growth deviations from runts (Lillehammer et al., 2013) and possibly diseases like pancreas disease (Føre et al., 2016). With the current experimental study employing repeated measurements per fish over a week of recording, it is feasible that arrested growth is detected on individual level but the lag in time required for recording individual growth with suitable accuracy would reduce management response time to sources of arrested growth.

The level of individual accuracy, strong positive correlation and high concordance of diode frame readings paired with PIT tag readers maybe uniquely suited to some precision fish farming applications. For instance, genetic evaluations require methods with suitably high throughput to record thousands of related individuals under the commercial conditions they are expected to perform. Furthermore, genetic evaluations are interested in the accuracy of the estimated breeding values which represent random solutions due to additive genetic variation of the actual measured traits. As a result, the accuracy of estimated breeding values increases when more relatives are recorded and when more individuals are repeatedly measured. However, diode frames measurements need to be significantly heritable, whilst repeatability is the upper threshold for heritability estimates (Falconer and Mackay, 1996). Heritability of diode frame measurements of e.g. body length and weight of any fish species has yet to be established.

4. Conclusion

In conclusion, diode frames can measure population level body length and weight of Atlantic salmon in sea cages with high accuracy. Furthermore, diode frame measurements on an individual fish level were repeatable and moderately concordant. By increasing the number of records per individual fish, the precision of measurement is increased resulting in strong positive correlations and high concordance. Diode frames measurements may hold promise for continuous growth measurements needed in genetic evaluations.

5. Ethics statement

All experimentation performed in this study were in accordance with the Norwegian ethical standards for research involving animals.

CRediT authorship contribution statement

G.F. Difford: Software, Formal analysis, Writing - original draft, Validation, Visualization. **S.A. Boison:** Conceptualization, Investigation, Methodology, Data curation, Funding acquisition, Writing - review & editing. **H.L. Khaw:** Investigation, Project administration, Writing - review & editing. **B. Gjerde:** Conceptualization, Investigation, Methodology, Funding acquisition, Writing - review & editing.

Declaration of Competing Interest

The authors declare that there is no conflict of interest. Solomon Boison is currently employed by MOWI ASA and this organization has no financial or other competing interests in this manuscript or its findings.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2020.105411.

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