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Fish abundance estimation with imaging sonar in semi-intensive aquaculture ponds

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A R T I C L E I N F O

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Multibeam sonar
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A B S T R A C T

To know the abundance of fishes and their size distribution in the semi-intensive rearing systems in traditional ponds is an aspect key to plan and manage efficiently the sales lots. Usually this information is obtained by means of sampling which mandatory supposes a direct catch and stressful and time consuming management of fishes. Therefore, in this work we propose the use of non-invasive procedures based on multibeam sonars or imaging sonars to count and size the fishes in the ponds. For that, we use a commercial technology portable-fixed multibeam imaging sonar and estimate the abundance in ponds of a gilt-head seabream (*Sparus aurata*) fish-farm from sonar image analysis and adapting statistical methodologies traditionally applied for bird abundance estimation. Additionally, a simulation software was developed to emulate the fish aggregation contained in the rearing ponds. This computer program allows the calculation of an abundance correction factor which depends on the transducer beam size in relation to the pond size. The results indicate that the estimation is as accurate as the obtained by the fishfarm manager using traditional sampling methods and additionally it is possible to obtain a realistic function of the size distribution which allows estimate the biomass by size contained in the rearing ponds.

1. Introduction

Nowadays, the semi-intensive aquaculture in traditional ponds (namely '*esteros mejorados*' or '*cultivo extensivo mejorado*'; improved extensive farming –IEF-) is one of the main rearing system in the Southern of the Iberian Peninsula, particularly in Andalusia region (Southern Spain). These fish rearing systems are approximately two thirds of aquatic production in this area (Gutiérrez-Estrada et al., 2012) which has made a significant contribution to the regional economy in recent years. On the other hand, in addition to the economic factor, these systems have a great importance from the conservation of natural areas because in many cases they develop their activities in very extensive abandoned salt exploitations which are reconditioned and maintained to yield in a sustainable way fishes of very high quality.

The sustainable production provides to IEFs a competitive position compared to more intensive systems because these systems are fitted within the Blue Growth Initiative which promotes the development of eco-systemic services and functions and the integration of all stakeholders (Soto et al., 2008; FAO, 2010, 2017; European Commission, 2011; Brugère et al., 2018). The final consumer, as a fundamental part of stakeholders, senses that the produced fish is a product of very high quality that is sustainably reared and environmentally friendly and therefore pays more for it. However, the consolidation of these systems as a solid and developed industry is highly dependent on continuous improvement and adaptation to make the installations more efficient and cost-effectiveness (Liu et al., 2013; Pulido-Calvo et al., 2014). This way, processes and procedures that facilitate the fish management in the ponds should be implemented while satisfying sustainability and productivity criteria established.

In this sense, a crucial aspect that can be in danger the economic viability in this kind of installations is the correct quantification and control of the number of fishes in the ponds. In this kind of installations

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the fishfarmers know how many fishes put in the ponds but they don't know the abundance and distribution of the biomass at the end of the growing season (between 2 and 3 years). This is because the number of fishes can significantly decrease and the growth rates can be very different between individuals. Several causes as the mortality induced by the infection of different pathogens such as bacteria, viruses and parasites (Pereira et al., 2011; Pellizzari et al., 2013; Essam et al., 2016; Moreira et al., 2017; Firmino et al., 2019), the predation by fish-eating birds like cormorants, herons or ospreys and the poaching can explain the decrease of the fish abundance in the ponds.

The tracking of the fish abundance of in these fishfarms is very complex. This is mainly a consequence of structural features and sizes of the ponds. Generally, the ponds have trapezoidal cross-section, variable size and water sheet (approximately between 250 m^2 for the smaller ponds and 25,000 m^2 for the biggest ponds), depths that oscillate between 1 and 2.5 m and waters with a turbidity above 25 NTU. These characteristics joint to a not automatized water management (Gutiérrez-Estrada et al., 2012) strongly hinder the samplings design to estimate the abundance. Occasionally, the fishfarmers put small trammel nets at the end of the pond to carry out samplings to evaluate the changes in growth. However, from these samples it is not possible to estimate the abundance of fishes. Therefore, there is a high degree of uncertainty associated to the abundance and biomass contained in the ponds at the end of the growth period which doesn't allow an effective planning and management of the sales lots.

In these conditions, the fish abundance estimation can be faced from different approaches. A traditional approach would imply the design of a sampling program which mandatory would suppose a direct catch, management of fishes and water sheet and the intervention of several workers during a time period relatively long. But this approach would only provide a snapshot of abundance and biomass in a particular moment and implies an unwanted management that could introduce stress factors in the fish stock. A plausible alternative to this approach is the use of non-invasive procedures with sensor systems based on optical technologies (Shortis et al., 2016; Amin et al., 2017; Tseng and Kuo, 2020) or sonar technologies like multibeam sonars or imaging sonars (Føre et al., 2018; Li et al., 2020).

In relation to sonar technologies, several authors have reported that this type of devices can be used to count and assess fish behavior (Moursund et al., 2003; Tiffan et al., 2004). For example, Holmes et al. (2006) used dual-frequency identification sonar (DIDSON) system to evaluate and count sockeye salmons (*Onchorhynchus nerka*) in stocks returning to spawn in the Fraser River (Canada). These authors reported that the regressions between the DIDSON counts and the visual count data obtained by means traditional procedures were statistically indistinguishable from the line 1:1 which allowed them to estimate in a very accurate way the number of fishes for each migration event. Also, Han et al. (2009) used DIDSON system to counting and sizing farmed yellowtail (*Seriola quinqueradiata*) of large size reared in sea net cages. These authors concluded that this sonar system could be used to efficiently account the number of big fishes in this type of fishfarms. On the other hand, Grothues et al. (2016) used the returns of high-frequency side-scan sonars connected to autonomous underwater vehicles (AUVs) which were programed to carry out missions conducted specifically for fish sonar reconnaissance. Their results showed that although this type of sonar is not specifically designed for this objective, it can be used to identify, to measure and to count fishes, particularly if the fishes are grouped forming schools.

Therefore, the main goal of this paper is estimate the abundance of fishes contained in rearing ponds of IEFs located in the Southern of Iberian Peninsula. For that, we use a commercial technology portable-fixed multibeam imaging sonar non specifically designed to count fishes. Additionally, we establish a second objective focused on the evaluation of procedures traditionally used for bird abundance estimation to estimate the abundance from the sonar images fixed in an observation point.

2. Material and methods

2.1. Study area

The study was carried out in one IEF located in the Southern of Spain (37°12′N, 6°59′W). Particularly, the fishfarm selected 'Salinas del Astur' is located close to Punta Umbría town in the province of Huelva (Andalusia region) and is devoted to gilt-head seabream (*Sparus aurata*) production. This is a small-medium size installation built on a former salina. Nowadays it has three ponds with a mean depth of 1.5 m and total water volume of 7000 m^3, 5100 m^3 and 7950 m^3, respectively (Fig. 1). The water is pumped from the Bota River which is a tidal tributary of Odiel River. In the ponds the seabream grow from a weight of 30–100 g to commercial weights (around 400 g).

A total of 15000 specimens of gilthead sea bream (*Sparus aurata*) with mean weight of 250 g and frequency distribution unknown were introduced in the central pond of 'Salinas del Astur' between July and December of 2019. On the other hand, the combined annual mortality rate (natural mortality combined with disease and bird predation mainly) is around 30% (fishfarm manager personal comment) which is a mortality level similar to the recorded by other IEFs in the South of the Iberian Peninsula. Therefore, in July 2020 the total abundance was ranged approximately from 10,500 and 12,375 fishes.

2.2. Data collection

The recording of data and images were carried out under real operational conditions. That is, all daily management activities (*i.e.* feeding or pumping) except harvesting and restocking were performed by fishfarm workers. A Garmin transducer LVS32 linked to Panoptix LiveScope™ system was used to collect sonar images. The Panoptix LiveScope™ system was operated in high frequency (1.1 MHz) and forward view mode. In this mode, the transducer beam swept across 135 degrees and 20 degrees wide, enabling to sample a fairly narrow portion of the water column. This allows to show in a plotter realistic and monochrome video image of fishes as they move through the sonar beam (Fig. 2). The images were obtained by means the plotter Garmin GPSMAP 722 with a 7″ connected to Panoptix LiveScope™ system. This plotter doesn't allow record video files of Panoptix LiveScope™ but it is possible obtain screen snapshots by a manual procedure and theses images can be stored in a MicroSSD card in png format with a resolution of 800 × 480 pixels. The shot-save plotter response time allows a maximum capture frequency of 0.2 shots s^{-1}.

At the same time that the sonar images were taken, physical and chemical of water quality were recorded. For that, a multiparameter probe HORIBA U-52 was used. Data of water temperature, dissolved oxygen, and turbidity were simultaneity measured each minute.

2.3. Images processing and data extraction

For the images information extraction a manual procedure assisted by a computer program was carried out. For that, we used the software LabelImg which is a graphical image annotation tool for labeling objects originally development by Russell et al. (2013). LabelImg is written in Python and uses Qt for its graphical interface. The user can label, identify and mark each fish signal with a box whose coordinates (*xmin*, *xmax*, *ymin*, *ymax*) are recorded in a XML file (Fig. 3).

Since the transducer beam was operated in forward view mode the height of the fishes were detected in all cases independently of the fish position in relation to the emission-reception axis of the transducer. The height of each fish was estimated from *ymax*-*ymin*. From this scaled difference the fish length and fish weight were inferred from a sample obtained in 'Salinas del Astur' as:

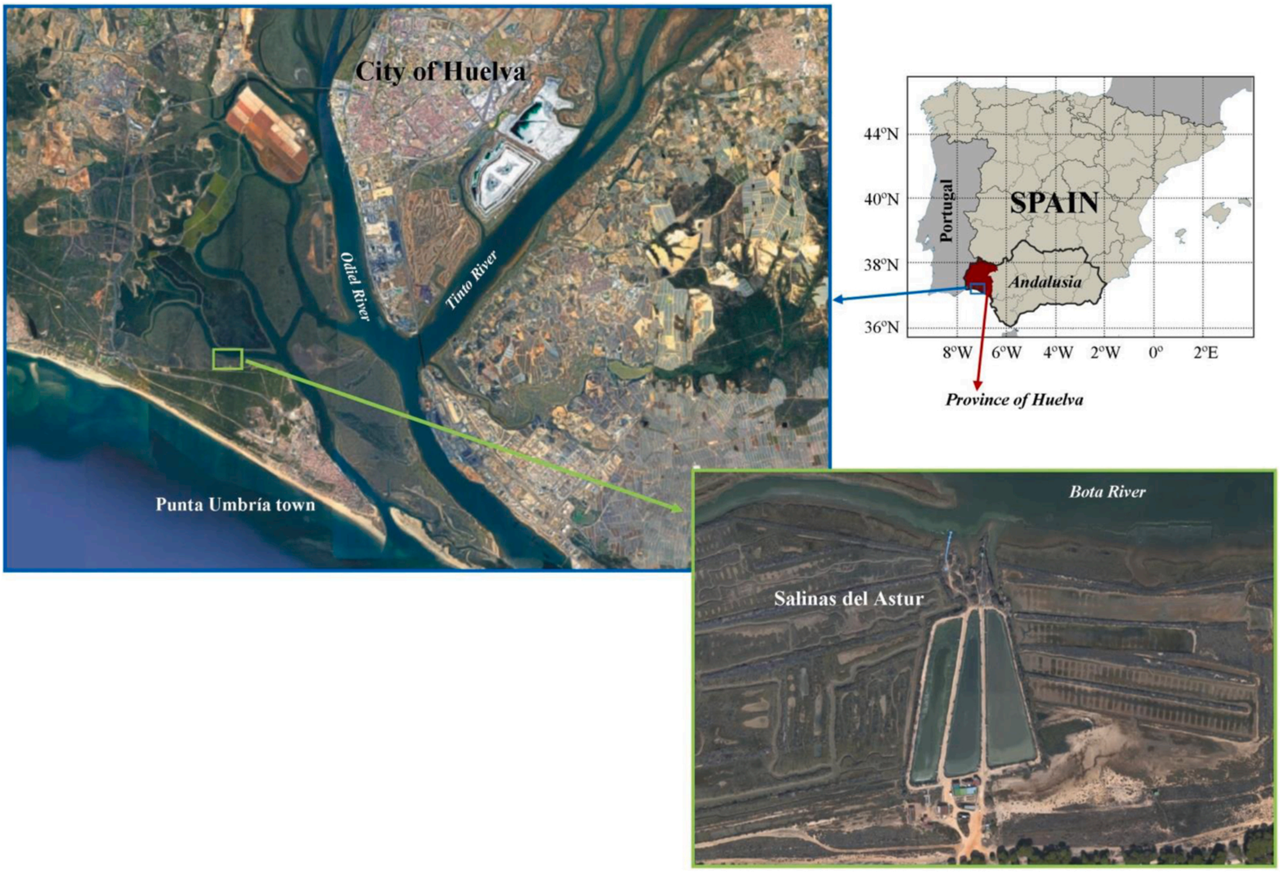

Fig. 1. Location of study area (fishfarm 'Salinas del Astur', Punta Umbría, province of Huelva, Andalusia region, Spain).

$$L_T = 2.7711 \cdot H + 2.3891 \ (n = 57;\ r^2 = 0.9387;\ p < 0.05)$$

$$W = 0.054 \cdot {L_T}^{3.31} \ (n = 57;\ r^2 = 0.9787;\ p < 0.05)$$

where L_T is the total length (cm); H is the height between the beginning of the dorsal fin and the beginning of the pelvic fins (cm) and W is the fresh weight (g).

2.4. Statistical procedure. Census station

The estimation of the abundance of a species by means of census stations procedures emerged as an alternative to transect methods for the evaluation of bird populations in steep and plotted areas, where it is very difficult to establish a progression line, or in habitats morphologically complexes where the detection of birds is very hard (Ramsey and Scott, 1979; Reynolds et al., 1980; Fancy, 1997). These methods provide visual count indices from data obtained for observers (or detectors) located in a fixed point or station. In this station the observer-detector records all specimens detected in concentric bands with prefixed width. The repetition of the sampling in different stations allows to obtain a contacts distribution by concentric bands and from these data it is possible to estimate the total abundance. The conditions in which these abundance estimation methods are applied are similar to the found in the rearing pond which makes it possible that they can be adapted to estimate the fish abundance.

This method assumes that the specimen detectability [$g(x)$= 1-cx] is a function of a constant c which in turn is depending of many factors (Robbins, 1981). In our case, c depends on relative position of the fish in relation to the beam swept and the capacity of the observer to differentiate between a fish and 'noise' in the sonar images. On the other hand, the estimation of the density (specimens m^{-3}) is based in the determination of a 'detectability cone' (Järvinen, 1978). The base of this cone is the observation circle (πc^{-2}). The mean detectability is the relation between the cone volume ($\pi/3c^2$) and the base area (πc^{-2}). This implies that approximately 2/3 (66%) of the specimens located into the observation circle will not be detected and therefore the estimated abundance index (n_t) must be corrected as $1.66 \cdot n_t$. This way, the estimated density in ponds from the abundance index can be defined as:

$$\overline{D}_t = 1.66 \cdot \frac{n_t \cdot 360}{\pi \cdot R^2 \cdot \alpha \cdot h} \quad (specimens \quad m^{-3}) \tag{1}$$

where $\overline{D}_t$ is the density estimated in a moment t; R is the transducer detection radius; α is the angle that determines the width of the transducer beam; and h is the mean depth in the pond (Fig. 2).

Two census points (C1 and C2) were established (Fig. 2). Each point was used as census station in different days (C1: July 16, 2020; C2: July 24, 2020). Each day, sonar images were recorded at five-minute intervals which supposed 78 counting periods. For each 5 min period, the mean of the observed fishes was calculated taking in account all images recorded in each period (fishes image^{-1} 5 min^{-1}).

Taking in account that the images were catched in two recording zones, assuming an exponential detectability function and 78 counting periods as independent events, the density in ponds can also be defined as (Sutherland, 2006):

$$\overline{D}_2 = \frac{(n_1 + n_2) \bullet \frac{\ln(n_1 + n_2)}{n_2}}{\pi k R^2} \quad (specimens \quad m^{-2}) \tag{2}$$

where $\overline{D}_2$ is the global density estimated in the pond; n_1 and n_2 are the number of fishes detected in the first and second zone, respectively; k can be equated to the number of counting periods; and R is the transducer detection radius.

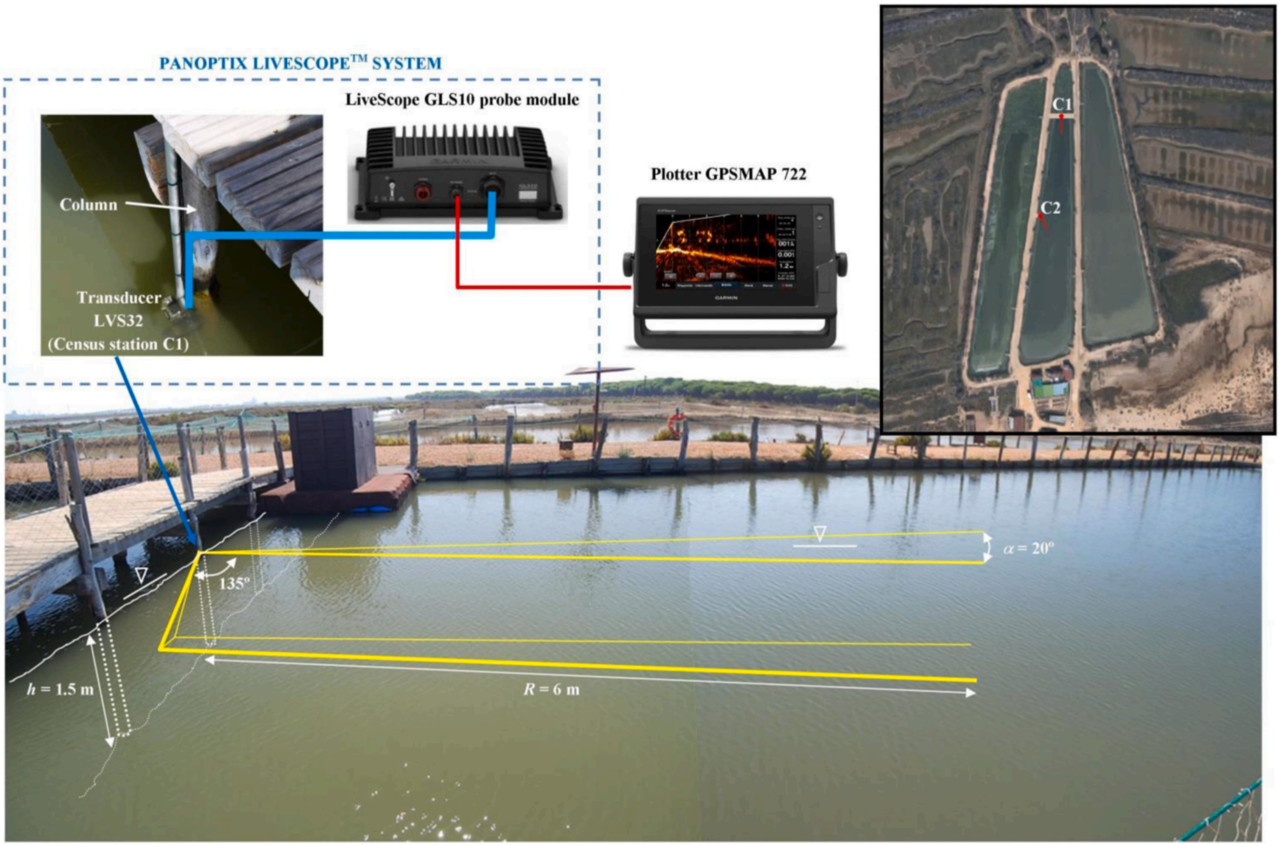

Fig. 2. Schematic representation of the Panoptix LivescopeTM System position in the central pond of 'Salinas del Astur' (census station C1) and its sonar beam. Top right, position and beam direction at census stations C1 and C2.

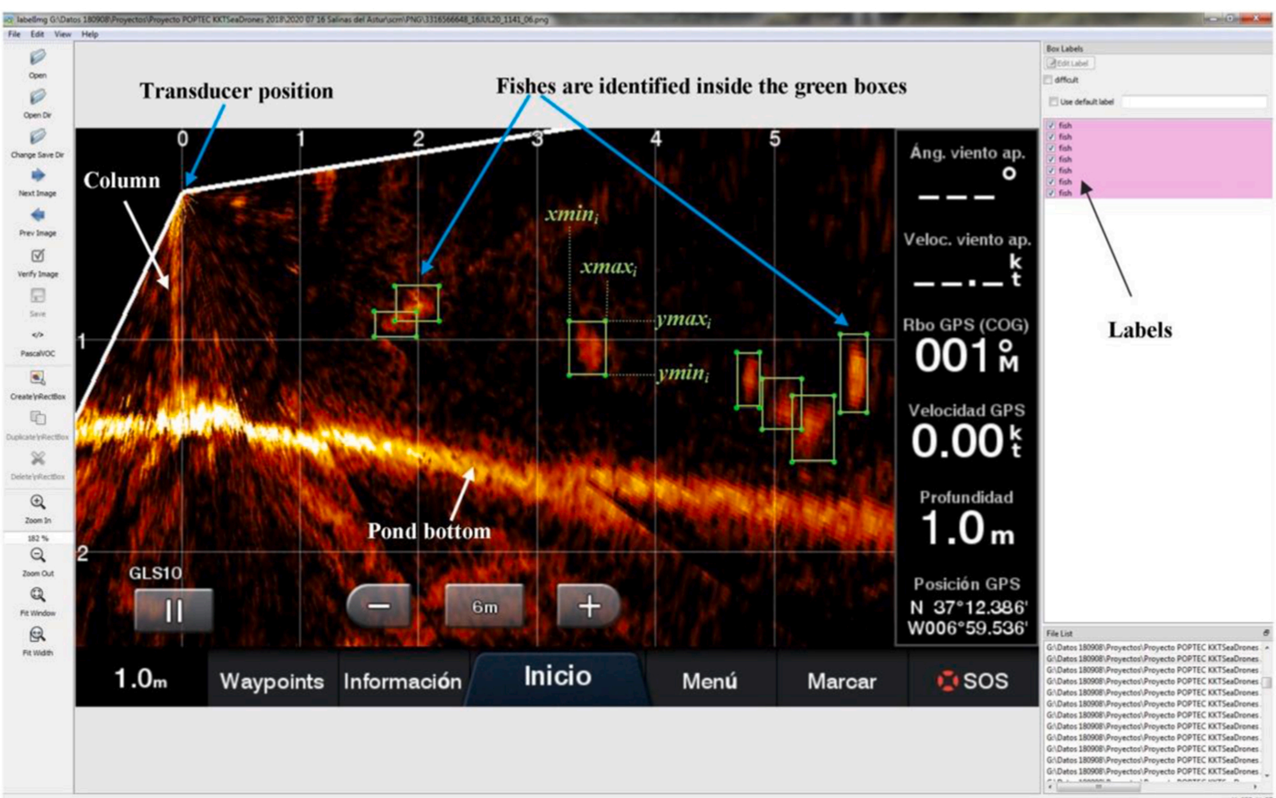

Fig. 3. Example of sonar image treatment with the software LabelImg.

The comparison between the estimated abundances from $\overline{D}_t$ and $\overline{D}_2$, and those provided by the fishfarm manager was done by means of a 'blind validation'. That is, the fishfarm manager was asked about the number of fishes in the pond after the abundance estimates were calculated from the sonar images obtained.

2.5. Correction factor of abundance index

The usefulness of an abundance index lies in its ability to provide information on the density of a species. This ability depends on the proportionality between the abundance index and the real abundance (Skalki and Robson, 1992). However, there are not experimental studies that establish proportionality relationships between the abundance index and the absolute abundance when the abundance index depends on detector size.

To estimate the variation of the proportionality between the abundance index and the absolute abundance in function of the detector size, a computer program that simulates the detection capacity of detectors with different sizes was designed. This program integrates a particles movement model development by Vicsek et al. (1995) −Vicsek model− . Assuming that any external stimuli that may influence the movement of the fish remain constant, the Vicsek's model can emulate the typical dynamic and aggregation behavior observed in the fishes contained in the rearing ponds.

In the Vicsek's model the fishes are represented by points moving continuously on the plane whose velocities ($\mathbf{v}_i$) were determined simultaneously at each time step according to:

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t)\Delta t \tag{3}$$

where $\mathbf{x}_i$ (t) is the position vector of a fish in a time t and $\mathbf{v}_i$ (t) is the fish velocity vector which was established by an velocity absolute value (v) and a direction that depends of an angle θ. In turn, θ in a moment t was obtained as:

$$\theta(t) = [\theta(t-1)]_R + \Delta\theta \tag{4}$$

where $[\theta\ (t\text{-}1)]_R$ is the average direction of the fishes velocities (including the fish i) included in a circle of radius R around the fish i and $\Delta\theta$ is a random value between 0° and 180°. The average direction was calculated as:

$$[\theta(t-1)]_R = arctan\frac{[sin(\theta(t-1))]_R}{[cos(\theta(t-1))]_R} \tag{5}$$

To evaluate the effect of the detector size, a computer program in Visual Basic 6.0 was designed (Fig. 4). This program integrates the Vicsek model and allows estimate the particles abundance in a simulated rectangular pond in function of the number of particles and the relationship between the pond (P) and detector (d) sizes. Simulations with 1000, 6000, 11,000, 16,000 and 21,000 particles and relationships d/P between 0.1% and 0.4% at 0.05% intervals were carried out. From the results of these simulations is possible to obtain a regression equation from which can be extracted a density correction factor (cf) depending on the detector size in relation to the pond size.

3. Results

3.1. Correction factor estimation of abundance index

To estimate the correction factor of the abundance index (cf) a total of 35 simulations with the Vicsek model were carried out. In all cases, the simulations indicated that the number of particles estimated from the particles observed by the detector were lower than the number of total particles included in the simulations. The linear regressions between the number of estimated particles (EP) and number of real particles (RP) show slopes lower than 1 and significant explained variances higher than 97% in all cases (Fig. 5a to g).

Taking into account that the central pond of 'Salinas del Astur' has an estimated volume of $P = 5100\ m^3$ and that the detector volume is $d = 6.28\ m^3$, this implies that the relationship $d/P = 0.18\%$. Therefore, assuming that the gilt-head seabream mobility in these rearing conditions follows a Vicsek's model, the estimation of the total abundance with a detector of 0.18% of pond size and a real abundance of 15000 specimens is approximately a 11% lower than the real abundance (Fig. 5c). This way, we can assume that $cf = 1.11$.

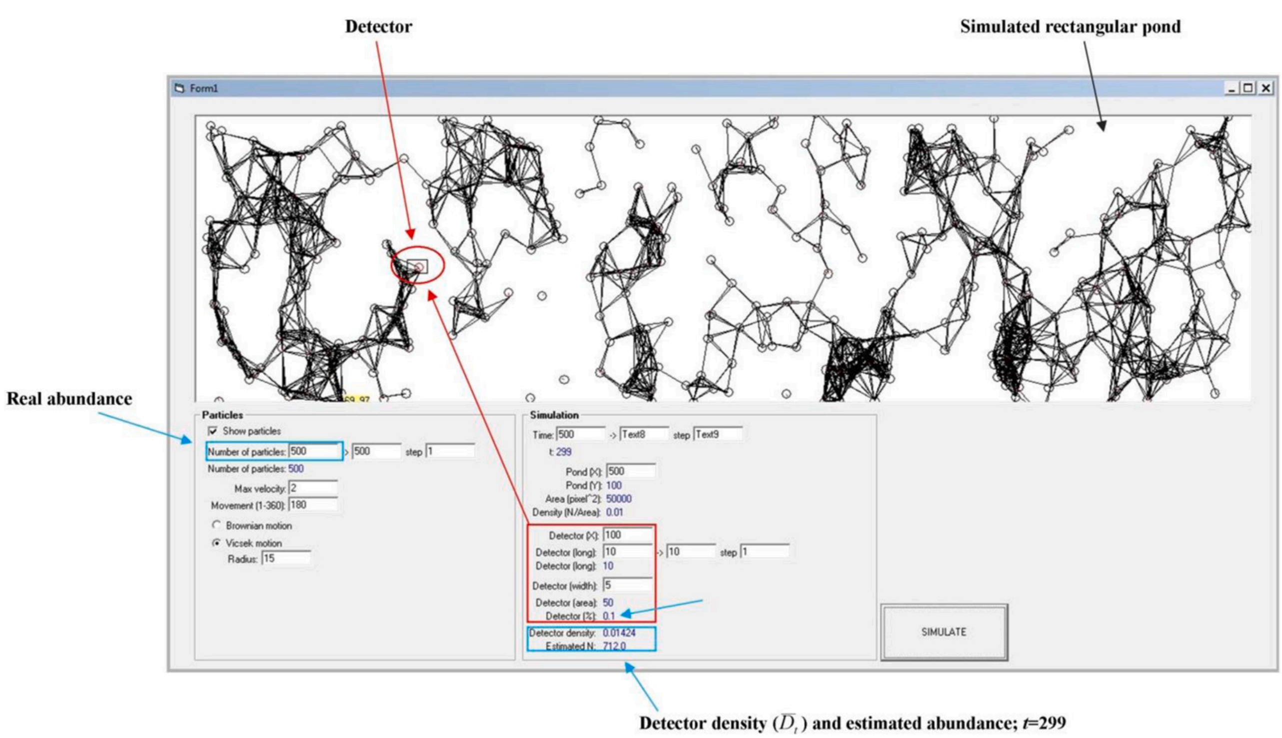

Fig. 4. Main window of the software to simulate the fish movement in the rearing ponds. This software integrates the Vicsek model.

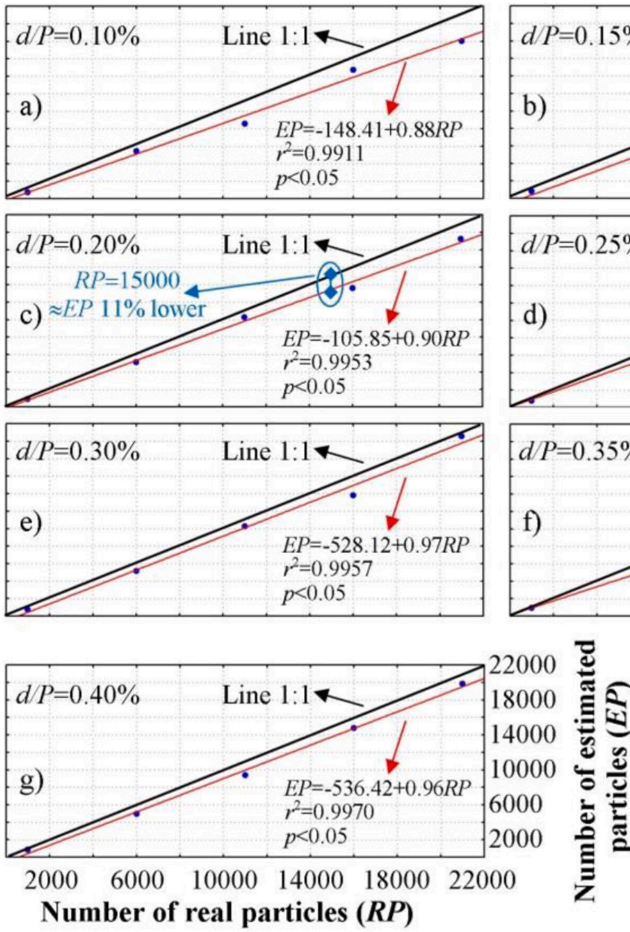

Fig. 5. Relationships between the real abundance of particles (*RP*) and the estimated number of particles (*EP*) for a *d*(detector size)/*P*(pond size) relation of: a) 0.10%; b) 0.15%; c) 0.20%; d) 0.25%; e) 0.30%; f) 0.35%; g) 0.40%.

3.2. Images and environmental factors processing

A total of 4003 images were recorded between July 16 (1851 images) and July 24 (2152 images), 2020. The mean of the number of fishes detected for each 78 five-minutes counting periods are showed in Fig. 6. The results indicate that the July 16 the maximum number of detected fished (between 25 and 30 fishes image^{-1} 5 min^{-1}) is observed in the first images (around 11:00 h). From this moment until the end of images recording, the mean number of fishes observed is stabilized between 5 and 10 fishes image^{-1} 5 min^{-1}. The mean number of detected fishes of the July 16 was 8.95 ± 6.16 fishes image^{-1} 5 min^{-1} and therefore the mean density for this day was 1.58 specimens m^{-3}. In July 24, the maximum number of fishes image^{-1} 5 min^{-1} is detected at the end of the morning (from 13:30 h) reaching similar values to the maximum observed for the July 16 (between 25 and 30 fishes image^{-1}). For this day, the mean of the detected fishes was 12.81 ± 5.62 which supposed a

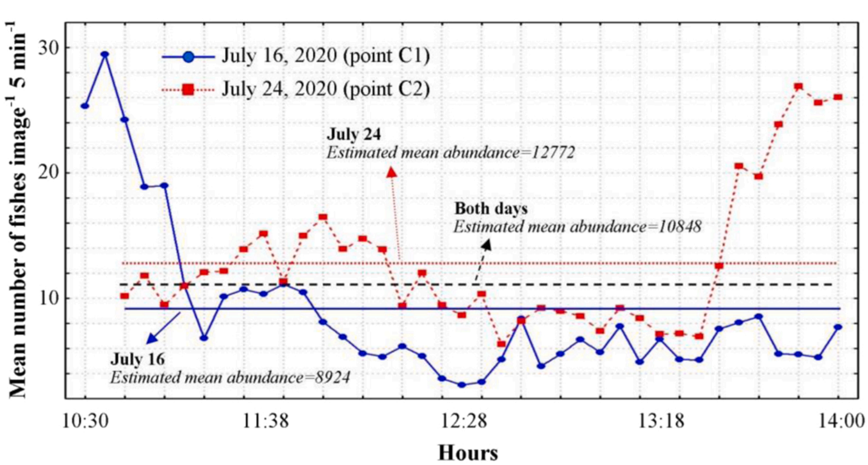

Fig. 6. Mean number of fishes detected for each 78 five-minutes counting periods. Continuous blue line is the mean number of fishes by image detected the July 16. Dotted red line is the mean number of fishes by image detected the July 24 and the dashed black line is the mean number of fishes by image considering both days.

mean density of 2.26 specimens m^{-3}. Globally, the mean for both days was 10.82 ± 6.17 fishes image^{-1} 5 min^{-1} ($\overline{D}_t$ = 1.90). This way, for the first day (July 16) the mean estimated total abundance in the pond was 8039·*cf* (8924) specimens and for the second day (July 24) the estimated abundance increased to 11,507·*cf* (12,772) specimens. This supposes that combining both days, the estimated abundance was 9719·*cf* (10,848) fishes.

Taking into account all recorded images, a total of 44391 fishes were identified (15,718 for July 16 and 28,673 for July 24) which supposes a theoretical recount rate between 1.44 and 2.24. Fig. 7 shows the frequency distributions by estimated size and density functions from sonar images for 16 and 24 July. The first day (July 16) a mean size of 18.13 cm and a mean fresh weight of 112.88 g were estimated. In the case of July 24, the sizes detected were higher (mean total length=24.95 cm; mean fresh weight=307.26 g). Globally, the mean total length estimated was slightly higher than 22 cm (mean L_T=22.54 cm) which was associated to a mean fresh weight of 238.14 g. From the estimated density functions is possible to calculate the total biomass in the pond. This way, for July 16 the total biomass estimated was 1007.34 kg and 3924.32 kg for July 24, which is an estimated mean biomass of 2508.31 kg. This supposes a mean density of 0.49 kg m^{-3} which is a normal density value for the traditional rearing ponds in the south of Spain and Portugal (between 0.2 and 2 kg m^{-3}).

Considering two recording zones and assuming an exponential detectability function with 78 independent counting periods, the estimated density in the pond was $\overline{D}_2$= 2.20 specimens m^{-2}, which taking in account the pond size suppose a total abundance of 11216·*cf* (12,450).

In relation to the environmental parameters, the profiles of the water temperature, dissolved oxygen and turbidity show the typical variations in these aquatic habitats (Fig. 8). In both days, the water temperature shows a positive trend with an increase of 1.5 ºC in a period of 4.5 h (from 28.3 ºC at 10:30 h to 29.7 ºC a 14:00 h). This water temperature increase implies low levels of dissolved oxygen which are kept at around 4.5 mg l^{-1}. On the other hand, the observed turbidity values (between 25 and 60 NTU) corresponding with waters with a low transparency as a consequence of a high concentration of phytoplankton and suspended solid. Also, significant differences were found in pumping in both days. July 16, the tidal coefficient at Punta Umbría was positive between 10:30 h and 14:30 h, which allowed pumping water into the pond. Instead, July 24 the tidal coefficient was negative during the morning and therefore, no pumping was made.

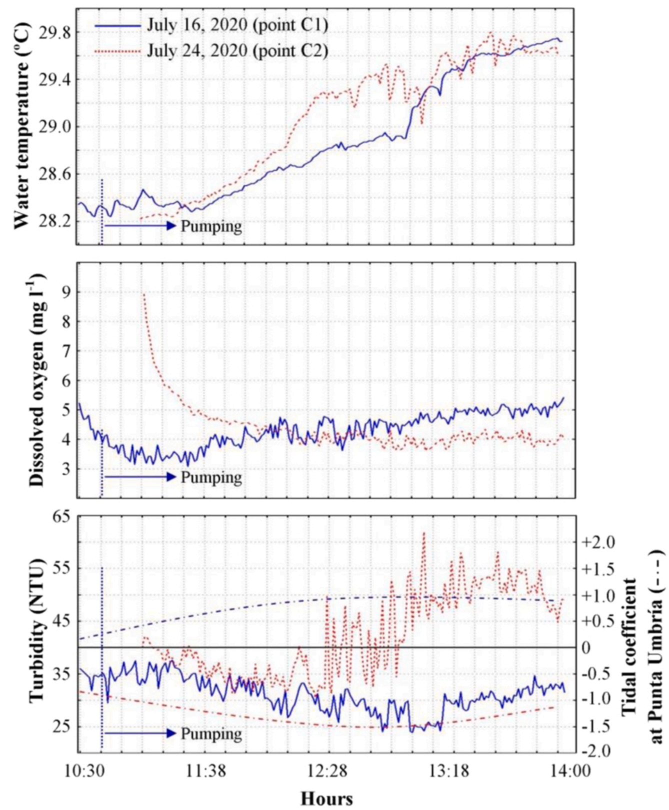

Fig. 8. Time series of water temperature (top), dissolved oxygen (middle) and turbidity-tidal coefficient at Punta Umbría (down). The start of the pumping on 16 July is indicated by the dotted blue line.

4. Discussion

Several very different techniques can be used to count and evaluate the total abundance: electrofishing, seine netting, trawling, lift-throw and push netting, hook and lining, gill netting, trapping, *etc.* These techniques allow to obtain samples from which is possible to estimate accurately the number of fishes of a stock, particularly if the population is confined. However, all these techniques have important disadvantages when are applied in rearing ponds. Their uses require the

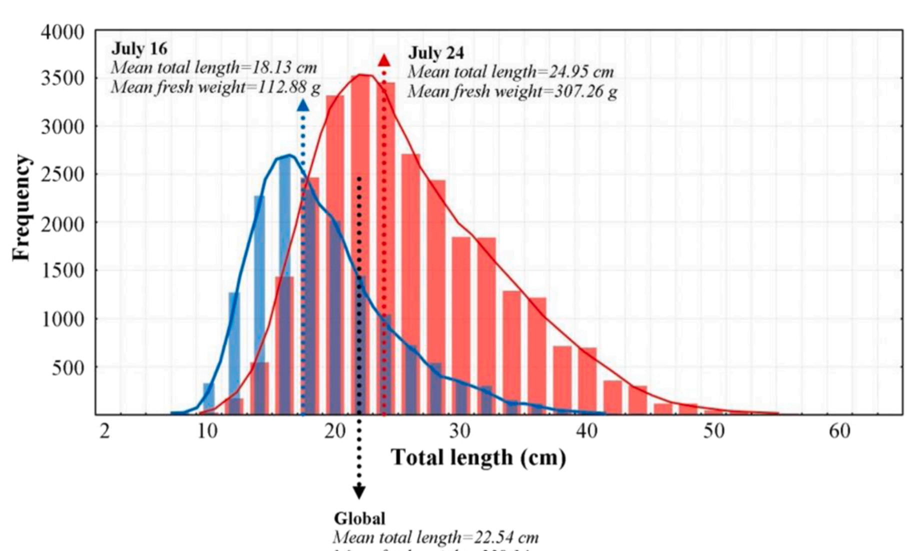

Fig. 7. Frequency distributions by size estimated and density functions from sonar images for 16 and 24 July.

intervention of several specialized workers, the fish management and a very time-consuming of sample post-processing. Likewise, the fish management can promote the emergence of stressful conditions which predispose fishes to diseases that result in very important economic losses (Ciji and Akhtar, 2021). Therefore, in this work the use of non-invasive techniques that don't require samples collection is evaluated as alternative procedure to estimate the abundance and the size-probability distribution function.

The obtained results with Panoptix LiveScope™ system could be equivalent to those obtained with other very popular imaging sonar systems like DIDSON or ARIS. Several authors have used these systems to count and evaluate fish size of different species in very diverse habitats (Braga et al., 2021). The basic difference between Panoptix LiveScope™ and others imaging sonar systems is that the system used in this work provides a vertical signal. This allows to obtain a relatively good measure of the total height of the fish but rarely is possible estimate the size in a direct way from the signal showed in the plotter. This force to transform the height signal to size by means an experimental equation which undoubtedly introduces biases in size estimates (Kimmerer et al., 2005). This is in line with reported by others authors as Lagarde et al. (2020) whom highlighted the importance of taking into account the biases in counts and size estimates in fish ecology and fisheries studies based on image sonars.

The bias size estimates depend of several factors. For example, Cook et al. (2019) reported that the accuracy depends highly on the fish size and their orientations in relation to the transducer beams. These authors identified that the measurement based on image sonar on relatively typical large-bodied fish like Snapper (*Chrysophrys auratus*) and trevally (*Pseudocaranx georgianus*) results in an accuracy of ± 1–10%. In fact, others authors as Han et al. (2009), Burwen et al. (2007) or Hightower et al. (2013) increase the error rate to ± 5–20%. This mean error on measurements as a consequence of the effect of beam spreading (don't tested in our work with Panoptix LiveScope™) could explain estimations of fish sizes relatively larger than expected, particularly for the July 24, 2021. For this day, fishes with 55 cm length were estimated when taking in account the initial mean lengths and the rearing period, these fishes could reach maximum lengths around 45 cm. This would suppose an estimation error close to 19% which is in the error range reported by Han et al. (2009), Burwen et al., (2007) or Hightower et al. (2013). On the other hand, an additional factor that can significantly increase the error in the fish size estimation is the manual assignment carried out by means the software LabelImg. When an image is processed with LabelImg, the reader assigns a rectangle enclosing the fish signal, but in several occasions the boundaries can be showed in the plotter in a fuzzy way. This is because the fish movements produce density changes and water ripples around the fish body which can be recorded in the snapshots. Therefore, the reader can assign a rectangle unusually high to some signals which, when are transforms to fish length, provide estimations of fishes higher than expected.

Also the count estimations are dependent on many factors. Among these factors, census method and their assumptions, fish density and activity, management conditions and time of day clearly condition the precision and accuracy of count estimations. In relation to the census method, the results of this work indicate that census methods traditionally used to count birds can be adapted to estimate number of fishes from sonar images. This way it is possible to affirm that, although nowadays and under operating conditions of the fishfarm is not possible to carry out a real validation of our results, the count estimation is at least as accurate as the one made by the manager of the fishfarm. However, for all these methods it is important understand the assumptions made because their violations may lead to erroneous conclusions. For example, it necessary to assume that fishes don't move from their location before. This is assumable because the number of fishes is directly counted from the sonar snapshot but obviously the number of fishes will increase longer one stay at a point and the lapsed time between snapshots is lower. This usually implies that densities will be overestimated (Bibby et al., 2000). This problem is saved using a short count period (5 min) and averaging the number of fishes detected in the snapshots for each period of 5 min.

Other assumption to take in account for these methods is the independent behavior of a fish in relation to one another. This assumption seems difficult to fulfill in the case of the fishes because schooling behavior is one of the most widespread forms of social behavior in fish for many species (Partridge, 1982; Pavlov and Kasumyan, 2000). Specifically the gilthead seabream is a schooling species which displays social hierarchies in terms of use of space and competition for food (Goldan et al., 2003; Montero et al., 2009; Oikonomidou et al., 2019; Arechavala-López et al., 2020). The violation of independent behavior assumption leads, in conditions of a relative high density, to underestimate the density and a possible non-linear relationship between the number of fishes detected and number actually present. This is in line with the results obtained in all simulations carried out with the Vicsek model which indicates that the underestimation when there is not an independent behavior could be around 10%.

Inevitably, the physical-chemical water conditions will play a very important role in the count estimation. Parameters as water temperature, dissolved oxygen or turbidity, between others, have a significant direct effect on fish physiology and consequently on fish movement. Finally, this will be reflected on the number of fishes that recorded in the sonar snapshots. Our results seems indicate that very high levels of dissolved oxygen (upper than 6 mg l^{-1}) would favor a low mobility of fishes in the pond (at least for the July 24) which could be a consequence of physiological stress conditions (Edsall and Smith, 1990; Salas-Leiton et al., 2009). This contrast with results obtained for the July 16 and the reported by others authors as Espmark et al. (2010). These authors indicated that one of the effects of water supersaturated with oxygen on intensive Atlantic salmon rearing system was the increase of mobility and the periods of hyperactivity of fishes. This way, it is possible that the detectability variation recorded is dependent of other factors as pumping. Pumping introduces clean water in the pond favoring a water oxygenation and removing toxic compounds for fishes as ammonia and nitrite. If pumping is not carried out, the concentration of ammonia and nitrites increases, which is associated with short-term physiological and behavioral changes (Palackova et al., 1990; Gutiérrez-Estrada et al., 2004). Israeli-Weinstein and Kimmel (1998) reported that the response of Carps (*Cyprinus carpio*) to sub-lethal ammonia concentration was to dive to the bottom of the tanks and stay there for a time period which increased with the ammonia concentration. This effect can be indirectly detected in our results as a significant increase of turbidity from midday of July 24 and the keeping of the dissolved oxygen at 4 mg l^{-1} level.

5. Conclusions

The results of this work indicate that the use of sonar images combined with estimation procedures used typically in the field of bird census can be extremely successful in the operation and management of the semi-intensive aquaculture in traditional ponds. The proposed methodology allows to the fishfarmers have a very close approach of the fish abundance (at least as close than the carried out by the fishfarmer from traditional methods) in a fast way, cost-effectively and avoiding the problems associated to the extraction of specimens and the direct management of the population. Additionally, the fishfarmer can count on a tool that provides the probability associated to the abundance by sizes contained in the ponds which allows an efficient planning and management of the sales lots.

However, although we have showed that the proposed methodology can be very successful for these rearing systems, we suggest some caveats and recommendations for further trials and testing. Firstly, it would be necessary to carry out an increased number of trials, mainly in relation to the number of census stations which would allow evaluate adequately the transducer position and the detector size effects. Likewise, other more accuracy estimation procedures that imply the displacement of the sonar along the pond and its implementation in small unmanned surface vehicles (USVs) or remotely operated vehicles (ROVs) should be tested. Secondly, a significant effort would have to be made in the automatic counting and measurement, which would undoubtedly require the use of deep learning techniques. Thirdly, it would be advisable to obtain results from simulations with more complex fish movement models and their field test which would provide save adequately the limitations imposed by the independence assumptions of the abundance estimation methods. Finally, more emphasis should be paid on the effect of several physical-chemical water variables (like ammonia, nitrite among others) not considered in this work on the movement of fishes in the ponds.

CRediT authorship contribution statement

J.C. Gutiérrez-Estrada: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Supervision, Project administration. **I. Pulido-Calvo:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Project administration. **J. Castro-Gutiérrez, S. López-Domínguez, A. Garrocho-Cruz:** Investigation, Data curation, Writing – review & editing. **A. Peregrín, F. Gómez-Bravo, I. de la Rosa-Lucas:** Conceptualization, Methodology, Software, Formal analysis, Writing – review & editing.

Declaration of Competing Interest

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

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