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Automatic, operational, high-resolution monitoring of fish length and catch numbers from landings using deep learning

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ABSTRACT

Informed fishery management decisions require primary input data such as the fluctuations in the number of fish landed and fish length. Obtaining these data can be costly if conducted by hand, which is the case for length data in most fisheries. This cost often implies reduced sample sizes, which may introduce biases and lead to information loss at, for example, the boat level. The recent boost in artificial intelligence applied to fisheries provides a promising way to improve the assessment and management of stocks. We present an operational system using a deep convolutional network (Mask R-CNN) coupled with a statistical model that automatically estimates the number and the mean fork length of dolphinfish (*Coryphaena hippurus*) caught in a Mediterranean fishery with a resolution of each landed fish box from each boat. The system operates on images of fish boxes collected automatically at the centralized fish auction. The statistical model corrects for biases due to undetected fish using the convolutional network and estimates the mean fork length of the fish in a box from the number of fish and the box weight, allowing for high-resolution monitoring of fishery dynamics during the entire fishing season. The system predictions were empirically validated and showed good accuracy and precision. Our system could be readily incorporated into assessment schemes. We discuss how this type of monitoring system opens new opportunities for improving fishery management.

1. Introduction

All fisheries should aim to exploit their stocks so that fishers' profitability is maximal over the long-term, which implies fishing at sustainable levels (Hilborn, 2007; Iudicello et al., 2012). Achieving this goal is not trivial and is urgently needed in several Mediterranean fisheries, which are experiencing a steady decline in fishers (Palmer et al., 2017). Although overexploitation may still be a concern in some Mediterranean stocks (FAO, 2020), other issues seem more critical in areas such as the Balearic Islands (Western Mediterranean), such as problems associated with commercialization (Maynou et al., 2013; Reglero and Morales-Nin, 2008). Small-scale fisheries represent over 80% of the fleet in the Mediterranean (FAO, 2020), and they are usually organized and managed in close contact with local authorities and companies. Irrespective of the strategy adopted to achieve resilient fisheries, critical elements for success include the availability of science-based evidence for assessing the stock, and implementation of effective mechanisms to quickly incorporate this evidence within a management plan, which should also be economically acceptable by fishers (through, for example, co-management; d'Armengol et al., 2018).

Thus, adopting proper management actions requires frequent monitoring of landings. Depending on the economic importance of the fishery or how difficult it is to study, only a few variables may be available (hence data-poor fisheries; Dowling et al., 2015). Fish length and the number of landed fish are among the most relevant variables for assessing stocks and conducting bioeconomic analyses (fish prize is often length-dependent; Reglero and Morales-Nin, 2008). The estimation of the length of landed fish is obtained manually in the vast majority of cases. Although the error involved in manually measuring fish is small, the costs of periodically monitoring fish length using a proper sampling design may not be affordable. This cost increases with an increasing number of species and boats, which is the case for many small-scale fisheries. Furthermore, the total landed biomass of a species, and not the number of fished individuals, is in many instances the only available measure of the landings. In the last few years, automatic and massive

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extraction of information from image or video files has facilitated a new era of data collection. These techniques also seem appropriate for extracting information from fish landings, and their use has been suggested as a way to revolutionize ocean sciences and fisheries (Malde et al., 2020). In this context, this work aims to demonstrate an operational system in which time series of the number of fish landed and the fish length distribution are automatically obtained from landing images.

As a case study, we selected the common dolphinfish (*Coryphaena hippurus*, Linnaeus 1758) fishery in Mallorca (Balearic Islands). Dolphinfish is a key commercial species in the Mediterranean, and it is captured by small-scale fisheries using fish-aggregating devices (FADs) (Massutí and Morales-Nin, 1997; Moltó et al., 2020). The Mediterranean FAD fleets account for approximately 30% of all moored FADs deployed worldwide (Morales-Nin, 2011), and in the Balearic Islands, the dolphinfish fishery constitutes the most important catch in weight of the fleet (Palmer et al., 2017). It is a seasonal fishery that targets the annual cohort resulting from the strong reproductive signal in early summer (Massutí and Morales-Nin, 1995). Newly hatched individuals grow extremely fast and attain approximately 60 cm in 5 months (Massuti et al., 1999; Moltó et al., 2020), and the growth progression of this main cohort can be easily followed in commercial landings (Lleonart et al., 1999). Current evidence suggests a single stock in the Mediterranean (Sacco et al., 2017; Maggio et al., 2019), which is currently unassessed. However, since 2019, it has been considered a priority species by the

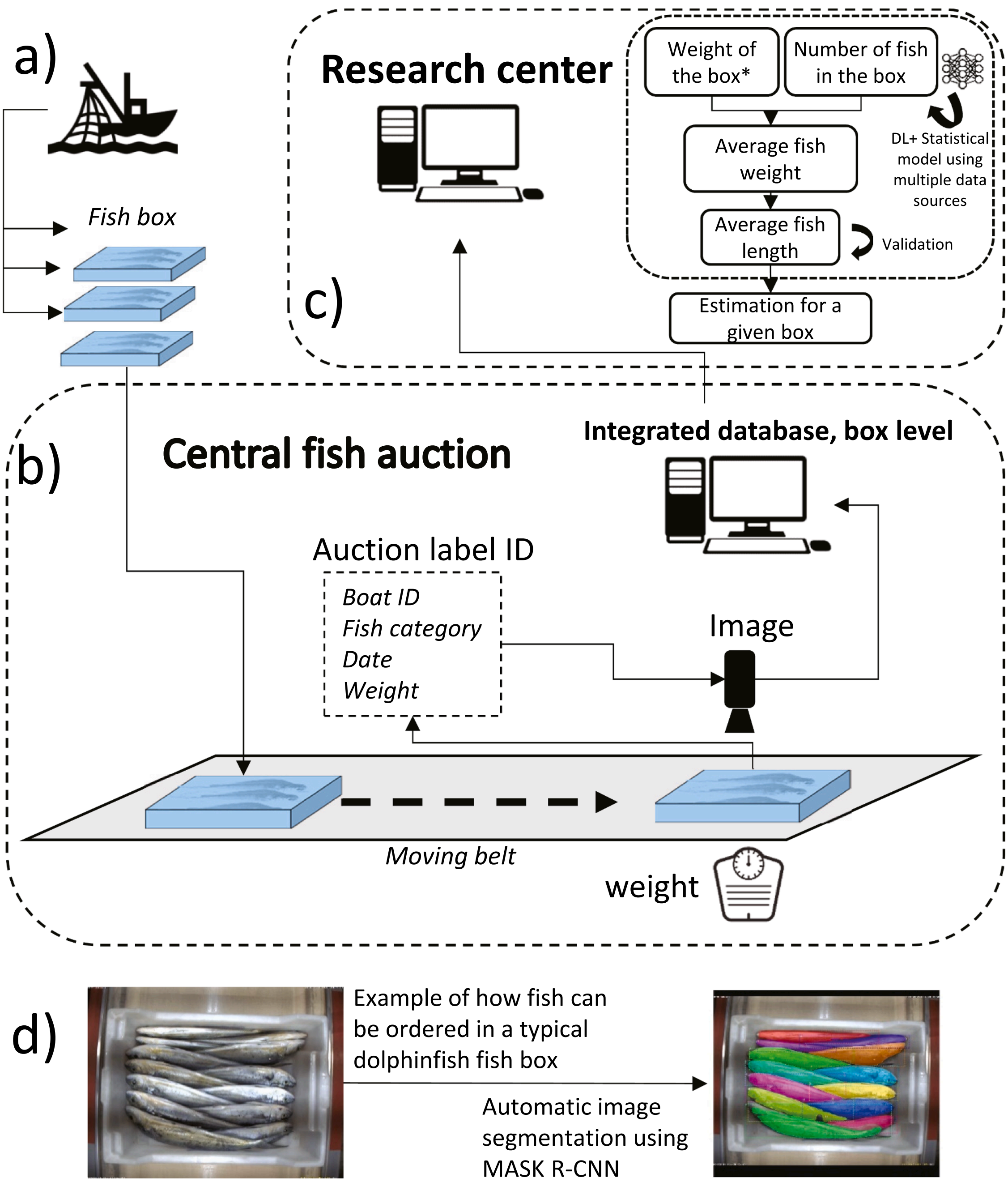

Fig. 1. Infographic of the general process used to estimate the average length of a fish box. (a) individual boxes classified by individual artisanal boats are sent daily to the central fish auction. At the fish auction, (b) individual boxes are automatically allocated a single boat ID containing boat, fish category, and weight information. An image is also taken from each box with a date stamp. Data are automatically integrated with the image at the fish auction and sent to the research center. (c) At the research center, the number of fish is estimated from segmented images using the Mask R-CNN technique (d) and corrected for biases, combined with the box weight and validated, to infer the average fish length in a box (see methods for further details). *Excluding the weight of the empty box.

General Fisheries Commission of the Mediterranean (GFCM), and a management plan has been called for by the FAO. This management plan includes richer monitoring of biological data and a better understanding of population dynamics (FAO, 2019; Moltó et al., 2020, 2021).

The use of artificial intelligence coupled with big data, and its application to marine science has evolved at a tremendous pace (Malde et al., 2020). Extracting data from images using artificial intelligence is an emerging field, although only a tiny fraction of the available information is being extracted and analyzed (Brett et al., 2020; Malde et al., 2020). Early image processing techniques have been replaced by methods based on deep learning (DL) (Lecun et al., 2015). This technique uses multilayer artificial neural networks and works optimally with big data. Since 2012, the use of graphical processing units (GPUs) has accelerated the implementation of convolutional neural networks (CNNs) (LeCun et al., 1998), which currently outperform humans in image classification tasks (Krizhevsky et al., 2012), leading to the current boom of DL. Since then, CNNs have been increasingly applied to the detection, classification, and segmentation of objects in images and video. Some of the most popular DL network architectures for object detection are YOLO (Redmon et al., 2016) and Mask R-CNN (He et al., 2017).

In the case of fish detection, the use of DL techniques is more recent, but it is rapidly increasing. In French et al. (2020), a CNN was designed to count fish in a video. Different network architectures have been used for fish classification (Chen et al., 2018; Meng et al., 2018; Villon et al., 2018), and Mask R-CNN has already been used to measure fish in images (Monkman et al., 2019; French et al., 2020; Álvarez-Ellacuría et al., 2020). However, progress is needed in operationalizing these tools, as most publications stop at the proof-of-concept level. As noted elsewhere (Malde et al., 2020), successful projects that apply DL in marine science exist (ICES, 2018), but the technology has not yet seen widespread deployment. In that context, fishery science can improve the costs of data acquisition, the amount of data, the resolution, and data availability used for monitoring, assessment, and management.

Accordingly, the general objective of this work is to demonstrate how to automatically extract massive information from images of landings using DL techniques. The specific objectives include i) estimating the number of fish in each landed fish box and ii) estimating the mean fork length of the fish in each box. The system is developed as a hybrid combination of Mask R-CNN and additional statistical procedures that obtains reliable figures at high resolution (i.e., fish box, boat and day, Fig. 1). We show how this highly-resolved, continuous data flow provides new ways to monitor landings at an unprecedented level of detail in data-poor fisheries.

2. Methods

2.1. Overview of the analytical strategy

We encountered some typical problems for many fish species: although dolphinfish are classified in single boxes, fish are ordered by fishers within a given box to optimize the sale at the auction. This means that fish are arranged in a single layer, but in many instances, only parts of the fish are visible (e.g., Fig. 1d). Thus, it is not possible to estimate the length of each fish (as was done in the case of *Merluccius merluccius*; Álvarez-Ellacuría et al., 2020). Conversely, the mean fork length of the fish in a box was estimated after combining (1) the number of fish in the box, (2) the weight of the box, and (3) the length-weight relationship. Both the weight of the box and the image were automatically generated when the box was auctioned and sent to our research center (Fig. 1).

The development of the operational system was achieved in several steps (Fig. 1). First, the DL algorithm using Mask R-CNN was developed and applied to the image of each box to extract an estimate of the number of fish per box. Second, a statistical model (hereafter, the *length model*) was developed to predict the mean length (total length, later converted to fork length) of the fish in a box from the weight of the box and the number of fish as estimated by the DL algorithm. Moreover, the *length model* allowed us to refine the estimate of the number of fish per box. Third, the *length model* was validated in terms of accuracy and precision when predicting the mean fork length of the fish in a box (i.e., the model predictions were compared against empirical measurements). Finally, the operational system (DL algorithm and *length model*) was systematically applied to each of the boxes of dolphinfish landed during 2020.

2.2. Images

The camera was placed top-down, just over the fish boxes, and images were captured when the conveyor was stationary. The camera system is currently operational and sends images of all the sold fish boxes each day. The daily number of fish boxes ranged from 700 to 1200. Data associated with each image (1153 × 708 pixels) included the boat, date, fish category (single species in each box, or a less informative category for mixed species), and weight. The boxes containing dolphinfish were automatically filtered. This species is never mixed with other species in a single box.

2.3. Deep learning implementation

We used Mask R-CNN (He et al., 2017) to detect and segment all visible parts of the dolphinfish in a box image. The implementation of Mask R-CNN used is available on Github (https://github.com/matterport/Mask_RCNN). The network uses pre-trained weights from the COCO dataset (a public dataset of images available at http://cocodataset.org/).

A total of 4117 dolphinfish from 276 images were manually segmented using the "Labelbox" online application (Labelbox, 2021). From these images, two sets were randomly separated in an 80/20 proportion (Alexandropoulos et al., 2019; 191 images were used for the training set, and 55 for a validation set). A third set consisting of 30 images was never entered into the model and was used as the test set. Based on conventional metrics (mean average precision, F1 score, recall, precision and accuracy; Ditria et al., 2020) the best performance was obtained with a training configuration setting of 88 epochs, with 190 steps per epoch, 60 validation steps and no use of image augmentation. The learning rate was set to 0.001. The implemented network and examples of the dataset used for training are available on Github (https://github.com/Evm7/coryphaena_detection).

Finally, after validation, the CNN's final performance when estimating the number of fish in a box (N_{box}) was evaluated on completely new images using the test set and the same performance metrics as above.

2.4. Length model

Estimating the mean length of a sample of fish (i.e., a box) from its weight and the number of fish in the sample (Fig. 1c) is not straightforward. Essentially, estimating the average length of a sample of fish from the sample weight using the species-specific length:weight relationship introduces a bias because larger fish contribute disproportionately to the weight of the box (Beyer, 1991; Nielsen and Schoch, 1980; Pienaar and Ricker, 1968; Ricker, 1958). Thus, it is necessary to account for the between-fish variability in length within each box.

The mean (μ_{box}) and the standard deviation (σ_{box}) of the length of the fish in a given box are the target parameters estimated from the box weight ($W_{box,}$ excluding the weight of the container, thus only reflecting fish weight) and the number of fish in the box (N_{box}). The expected distribution of the summed weight of all fish in a box (W_{box}) can be expressed as a function of μ_{box}, σ_{box}, N_{box}, and the parameters of the length-weight relationship (a_{LW}, b_{LW} and σ_{LW}). The derivation of this function is fully detailed in Appendices A, B and C. The real number of fish in a box (N_{box}) is expected to be related to the number of fish estimated from the deep learning algorithm ($NDeep_{box}$). We used a simple Poisson regression to model this relationship. For a summarized table of the parameters of the *length model*, see Table A.1 in Appendices A,B,C,D and E.

2.5. Empirical measurements

Unfortunately, in our case, the parameters of the length:weight relationship (a_{LW}, b_{LW} and σ_{LW}, Appendix A) cannot be directly estimated using the fork length (FL). Provided that the image and the weight of the boxes are obtained automatically during an auction, it is logistically impossible to stop the auction process long enough to manually measure the fish in a relevant sample of boxes. The chosen alternative was to combine several datasets:

A) A small sample of fish (n = 39) from which the total length (*TL*) was measured manually, both with an ichthyometer (TL_{ict}; instrumental precision: 1 mm) and on the image (TL_{img}).
B) A second sample of fish (n = 196) for which the weight (*WFish*, instrumental precision = 0.1 g) and *TL* were manually measured for each fish using an ichthyometer (TL_{ict}).
C) The relationship between the actual number of fish in a box and the number of fish estimated by the DL algorithm was established from a sample of 311 boxes for which the number of fish was determined both manually by an observer and using the DL algorithm.
D) The fourth sample of fish enabled us to estimate the within-box variability in fish length and evaluate whether this within-box variability was related to the mean length. In this case, we measured the TL on the fish box images (TL_{img}) for 508 fish from 83 boxes. The median number of fish measured per box was six, with a range between five and nine. In addition, and provided that W_{box} and $NDeep_{box}$ were also available for those 83 boxes, this fourth dataset enabled us to validate the *length model* (i.e., to compare the observed versus the estimated mean length for a box in terms of accuracy and precision). Note, however, that the latter variable is not used as an input to the *length model*. Instead, the expected mean of the length of the fish in a box is derived from the number of fish in the box (estimated from the deep learning algorithm) and the box weight (provided by the company).
E) Finally, fork length (FL_{ict}) is the preferred measure of body length for this species (Moltó et al., 2020). However, FL_{ict} is a particularly difficult variable to measure on the images due to the arrangement of the fish inside each box at the auction. Therefore, to estimate the mean length per box on the scale of the FL_{ict}, a fifth sample of fish (n = 166) was used, for which both the TL_{ict} and the FL_{ict} were measured with an ichthyometer.

The equations linking these datasets are detailed in the Appendices A, B and C.

2.6. Estimation of the length model parameters

The parameters μ_{box} and σ_{box} were estimated from W_{box} and the number of fish per box as estimated by the DL algorithm ($NDeep_{box}$) using a single (integral) Bayesian statistical model (i.e., the *length model*). This integral model also included the equations needed to link the five datasets considered in Section 2.5. The parameter μ_{box} for a given box was assumed to be normally distributed around a daily mean with a daily standard deviation (i.e., the *length model* is hierarchical with boxes nested within days). Samples from the joint posterior distribution were obtained using STAN (Stan Development Team, 2021) and the *rstan* library from the R statistical software (R Core Team, 2020). Several preliminary frequentist analyses were performed to inform the *priors* of all the auxiliary parameters (Appendices A, B and C), which are assumed to be normally distributed around the (frequentist) point estimations with standard deviations 100 times larger than the (frequentist) uncertainty (standard deviation). In a preliminary analysis, the measured standard deviation of the fish length in a box (i.e., the between-fish variability) was found to be independent of the mean length (83 boxes from dataset D; Fig. 2). Moreover, standard deviations were found to be gamma distributed (*fitdistrplus* R library (Delignette-Muller and Dutang, 2015)). Thus, σ_{box} for any new box has been assumed to be a random sample from such a gamma distribution (shape = 6.93; rate = 2.48). Four independent chains were run using the NUTS algorithm from STAN. Posteriors were defined by 10,000 iterations, after 10,000 warm-up iterations for model validation and 1000 iterations after 1000 warm-up iterations for predicting new boxes when analyzing the entire fishery (see below). The model's convergence was inspected both visually and using the Gelman-Rubin diagnostic (Rhat statistic; Stan Development Team, 2021). Any additional details regarding the model structure are available in an R script provided in Appendix D. The input data are also available in Appendix D.

2.7. Analyzing the entire fishery

Dataset D in Section 2.5 allowed us to compare, in terms of accuracy and precision, the *length model* predictions for the mean length of the fish in a box (μ_{box}) for 83 boxes against the mean length of a fish sample measured from each of those boxes. After successful validation (Results section), the *length model* can be used to estimate the number of fish and the mean length of any new fish box.

As a real-world application, we estimated the mean fork length of each of the boxes of dolphinfish landed during the 2020 fishing season. This estimation implied the analysis of 10,673 fish boxes from the onset of the fishery (August 25th) until the effective end of the FAD fishery. We also estimated the total number of fish landed per day and their fork length (and weight) distribution. Finally, as an example of how these high-resolution data can be exploited, we graphically inspected the individual boat's daily fishing activity in relation to the fork length.

3. Results

The performance of the Mask R-CNN when estimating the number of fish in a box was satisfactory overall. The resulting values for the selected performance metrics were: mean average precision = 79.8%, dolphinfish-level precision = 96.06%, dolphinfish-level recall = 90.54%, F1 score = 93.21%, and model accuracy = 86.10%.

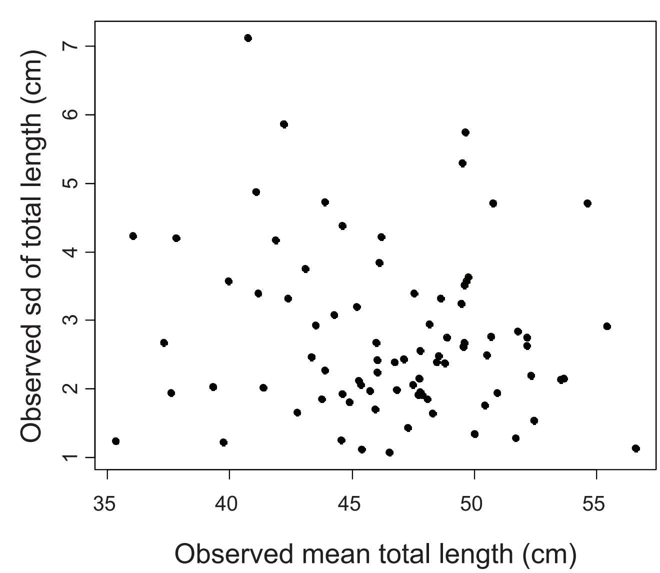

Fig. 2. Lack of relationship between mean length and standard deviation for the fish from 83 boxes (dataset D).

All the parameters of the *length model* were successfully estimated (technical details (Stan Development Team, 2021): there were no divergences, the Expected Bayesian Fraction of Missing Information (E-BFMI) indicated no pathological behavior, the Rhat was always between 0.99 and 1.01, and the effective number of samples for model parameters was always larger than 10,000; the effective number of samples for any μ_{box} was also larger than 10,000). The parameter values and their uncertainty are provided in Appendix E.

Regarding the validation of the *length model*, the estimates of the μ_{box} estimated from W_{box} and $NDeep_{box}$ were compared with the mean length of the fish in a box actually measured from 83 boxes. Note again that the latter variable has not been used to either estimate the parameters of the *length model* or to predict the mean length of the fish in a new box. The values predicted by the *length model* were close to the actual measured values, without apparent bias (Fig. 3). The accuracy of the μ_{box} estimates, which was quantified by the square root of the mean squared deviation (RMSD), was 2.4 cm, ranging from 6.9% for a 30 cm fish to 4.0% for a 60 cm fish. The deviations between the observations and estimates ranged between − 7.4 and 4.8 cm with 95% of the cases between − 5.6 and 2.4 cm. The precision of the μ_{box} estimates, quantified from the mean of the 95% credibility interval range, was 1.2 cm. The estimated (by the *length model*) number of fish per box is also close to the observations. The accuracy, quantified from RMSD, was 1.7 fish, with 95% of the deviations oscillating between − 3.3 and 3.7 fish. The average precision (mean of the 95% credibility interval range) was 0.7 fish. The actually observed range of the number of fish per box was between 1 and 26 fish. Therefore, the *length model* was satisfactorily validated.

The *length model* was applied to any new landed box to estimate the mean fish fork length in all boxes in the fishing season. Thus, the *length model* predictions can be aggregated by day, boat, or at any needed level. The temporal evolution of the mean fork length of the fish in a box at the day level is shown in Fig. 4. The median of the mean fork length of all the boxes landed in a day (Fig. 4a) ranged from 38.3 cm (95% CI between 36.3 and 40.3 cm) at the start of the season (September 1st, 2020) to 55.1 cm (53.1–57.1 cm) toward the end of the season (December 1st, 2020). The number of boxes landed per day dropped significantly toward the end of the season, which explains why on some days, the median of the mean fork length of the fish in a box is smaller than what could be expected from the general trend. Provided that both the mean fork length of the fish, its standard deviation and the number of fish have been estimated for each box, the fork length variability at the fish level can be assessed using bootstrapping (i.e., randomly sampling the proper number of fish from the fork length distribution of a given box, and summing the results for all the boxes landed in a given day). The results of this bootstrapped exercise suggest that the figures at the fish level (i.e., pooling all fish landed in a given day; Fig. 4b) were similar to those at the box level but with larger variability: from 37.6 cm (28.8–46.8 cm 95% CI) at the start of the season to 55.0 cm (44.7–65.1 cm) towards the end of the season (using the same dates as before). The estimated number of landed individuals (Fig. 4c) decreased from 3698 fish (3558–3.847 fish 95% CI) at the start of the season to only 269 (232−308) at the end of the season (using the same dates as before). The reported weight (the sum of the weight of all boxes in a given day; Fig. 4d) ranged from 2141–451 kg. The total biomass landed in 2020 was 98,694.6 kg.

As an immediate application of the monitoring system presented here, Fig. 5 shows the daily pattern of the mean fork length of the fish in a box at the between-boat level. Most of these artisanal boats fish every day (except weekends) and were probably FAD boats (identity not shown for confidentiality) because other fishing modalities are banned to this fleet at the time that dolphinfish are being caught (Legal mandate Orden OAA/1688/2013). The intentional capture of dolphinfish using gears other than the modified purse seine around FADs are unlikely but not impossible. More interestingly, some of these boats (i.e., the first seven boats that registered landings during the first week in Fig. 5) consistently landed slightly larger dolphinfish at the start of the season. This type of data provides the possibility to retrieve useful information on spatial catch patterns (see Section 4).

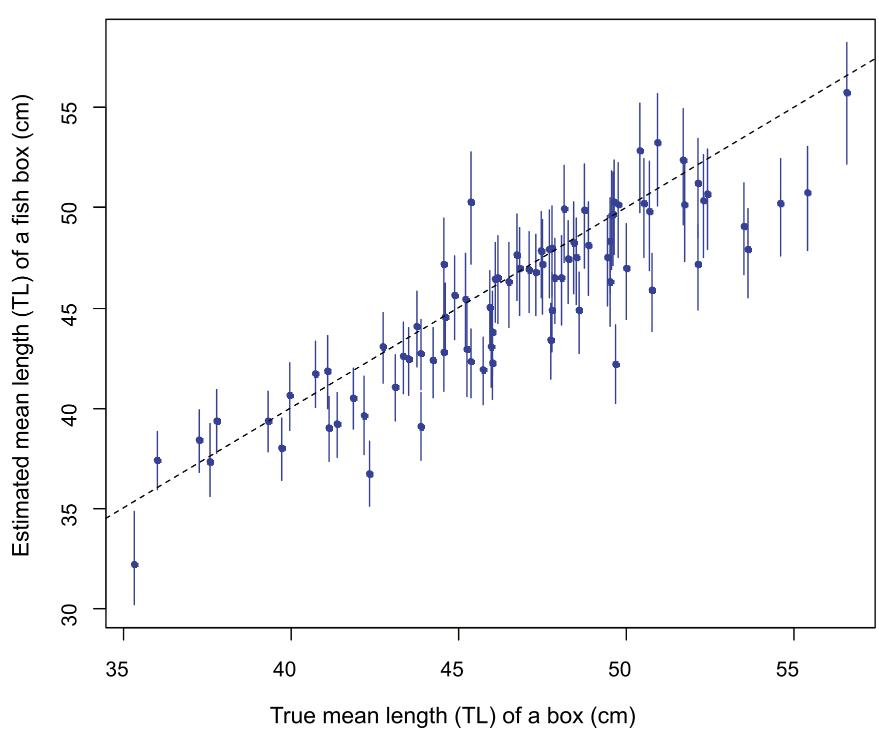

Fig. 3. Model validation: comparison of the observed versus estimated average length (TL_{img}) for a sample of the fish in 83 boxes (dataset D). There is no evidence for bias. The accuracy of model predictions (RMSD) was 2.4 cm. The precision (mean of the 95% credibility interval range) was 1.2 cm.

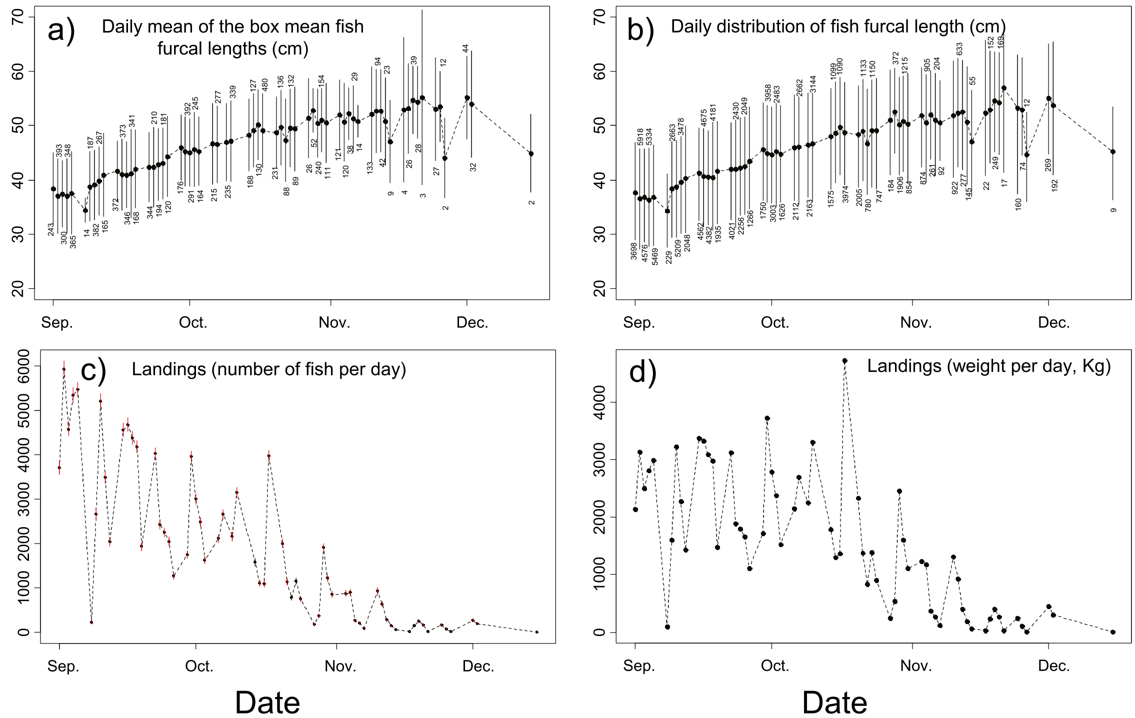

Fig. 4. Temporal patterns of the fish length and number of fish landed at the day scale. (a) Mean of the estimated median length for all the fish boxes landed in a given day (bars are 95% CI). (b) Mean of the estimated length for all the fish landed in a given day (bars are 95%CI). (c) Estimated number of fish landed. (d) Reported landed weight (summed from box-reported weights). Numbers in (a) and (b) are the sample sizes for the boxes and fish, respectively.

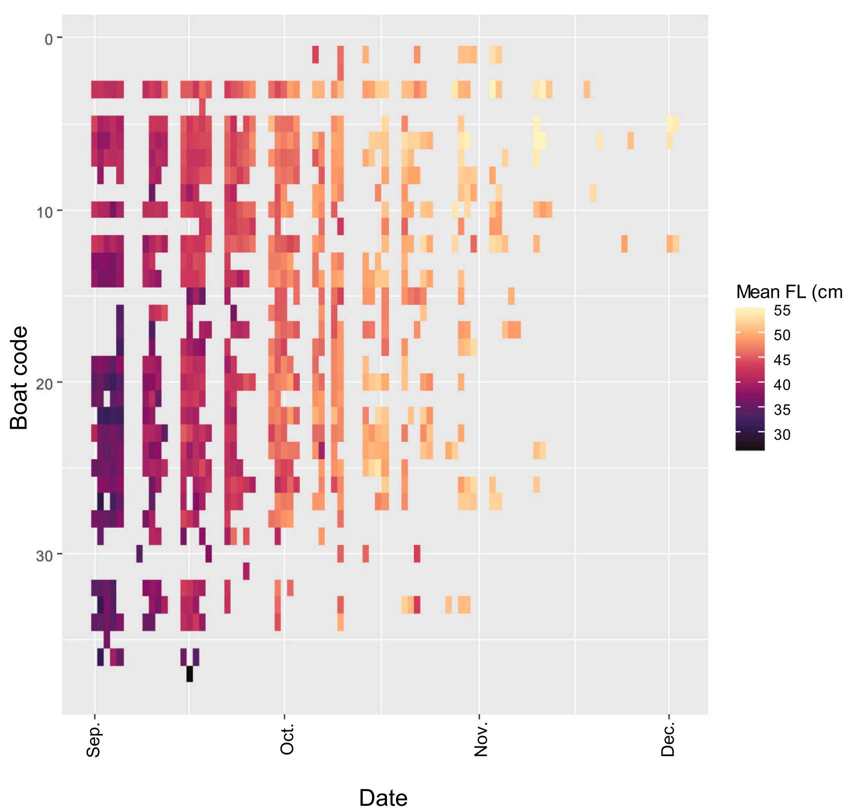

Fig. 5. Heatmap of the estimated average dolphinfish length landed per boat and day during the 2020 FAD fishing season at the Mallorca central fish auction. The boat's identification is coded for confidentiality. Only boats yielding at least 30 measured (using deep learning) fish per day for length estimation were considered. Note the gaps attributed to weekend fishing prohibition.

4. Discussion

We present the results of an operational system combining a deep convolutional network (Mask R-CNN) and a statistical model that automatically and reliably estimates the number of dolphinfish caught in a Mediterranean fishery as well as the average fish length with a resolution of the fish box from each boat. Our system, which has been fully operational since 2020, required developing a statistical approach that dealt with fish partial occlusions, unobserved fish, and biases related to the nonlinear relationships between length and weight in a fish box. We briefly discuss the benefits of the system, avenues of improvement, and future applications.

Our estimate of the mean fork length for the fish in a box relies on estimating the number of fish per box and the box weight. The estimated vs. the observed number of fish per box was reasonably similar, and the integrated number of fish per month falls within the typical ranges of previous work in the Balearic Islands (FAO-GFCM, 2004). The estimates of the mean fork length for all the fish landed in a day fall well within known values in the literature for this fishery estimated using traditional methods (Lleonart et al., 1999).

The current data needed for preliminary evaluations of this species in the Mediterranean are based on depletion models running at monthly timesteps (FAO, 2016), which need data on the number of landed individuals and average length. Our system demonstrated reasonable accuracy and precision in estimating the length distribution and number of individuals from the box images at narrower time steps (days). Furthermore, given the large differences in average fish length between months, we contend that our system can adequately satisfy the data requirements at the month resolution, which will be needed to implement stock assessment as recommended by the GFCM (Recommendation GFCM/43/2019/1).

The DL algorithm used herein was a modification of an existing architecture and proved efficient after training. One potential step forward would be to shift from fine-tuning generalist CNNs, such as that in the present work, to building more specific nets for the fisheries community. This goal could be achieved within collaborative projects. Further refinements in the statistical analysis should focus on increasing the datasets used for relating fish weight and fork length. Specifically, the ideal scenario for improving model validation would be to directly measure the fork length for a relevant sample of fish per box from a relevant sample of boxes, but in our case study (and probably in most other cases), the auction logistics preclude this. As long as this constraint remains, combining several datasets is inevitable; thus, the precision of the *length model* predictions could be improved by enlarging the size of all the datasets involved.

One of the system's advantages that may come at the cost of decreased precision at the fish level is the ability to process massive amounts of data at the resolution of individual boats and days. The dolphinfish fishery in this region is based on the seasonal exploitation of the annual cohort recently recruited to the fishery (Moltó et al., 2020). The fine-scale analysis of cohort composition between years is one potential direct application of our system. This application may be relevant in the face of known and projected environmental effects on this fishery based on age-0 individuals (Moltó et al., 2021; Rambo et al., 2021). On the other hand, fishers have individual FAD lines (20–40 moored FADS each) allocated by law at geographically fixed areas each year, in transects extending orthogonally to the coast for several miles around Mallorca Island (Lleonart et al., 1999). The Balearic Islands have a complex coastline, and different water masses dominate in the north and south, with substantial temporal and spatial variability (Balbín et al., 2014). Furthermore, this is a highly mobile species, and targeted juveniles might have slightly different origins with regard to their environmental history. Thus, it is likely that dolphinfish spawning and growth exhibited some differences at a relatively small geographic scale; these differences could be linked to the ports where each of the boats operates. The present system would enable such investigations in this and other species. Furthermore, analyses linked to the economic value of the product in relation to the length of the fish sold at auction could be explored thanks to this box-level resolution. The automatization of data collection and its usefulness in fishery management are clearly illustrated by remote electronic positioning systems such as AIS (McCauley et al., 2016). Further integration of these spatial data with boat-level biological data using automatic systems such as ours is foreseen in the near future.

The application presented could also have ramifications for the blue economy. For example, traditional methods for obtaining length samples typically rely on the manual measurement of fish. This implies tedious and costly work devoted to manual sampling but also lower working qualifications. The use of a high-resolution automated system such as that presented here, once established, could foster highly-formed employment (e.g., TIC, data analysts), and these employees could improve, maintain and expand this system to more species, ports and areas.

CRediT authorship contribution statement

Miquel Palmer: Funding acquisition, Conceptualization, Statistical analysis, Visualization, Writing – review & editing. **Amaya Álvarez-Ellacuría:** Hardware-software implementation, Data acquisition, Validation, Editing. **Vicenç Moltó:** Writing – review & editing. **Ignacio A. Catalán:** Conceptualization, Writing – original draft preparation, Visualization, 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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Appendices A To E. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fishres.2021.106166.

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