

## Article

# Drone Surveys Are More Efficient and Cost Effective Than Ground- and Boat-Based Surveys for the Inspection of Fishing Fleet at Harbors

José Amorim Reis-Filho <sup>1,2,\*</sup>  and Tommaso Giarrizzo <sup>3</sup> 

<sup>1</sup> ICHTUS Ambiente & Sociedade, Salvador 41830-600, BA, Brazil

<sup>2</sup> Graduate Studies Program in Ecology: Theory, Application and Values, Federal University of Bahia, Salvador 40170-115, BA, Brazil

<sup>3</sup> Instituto de Ciências do Mar (LABOMAR), Universidade Federal do Ceará (UFC), Fortaleza 60020-181, CE, Brazil

\* Correspondence: amorim@ichtusambiental.com.br

**Abstract:** Generating accurate estimates of the number of vessels in fishing ports using traditional methods (i.e., ground- and boat-based) can be challenging as observations are distorted by an horizontal perspective. Automated inspection using drones is an emerging research alternative for this type of investigation. However, the drone-based and ground- and boat-based survey methods have not been quantitatively compared for small-scale and commercial fishing fleets in their ports. The objective of this study was to determine the number of fishing vessels and detect onboard fishing gear using three independent sources of data along 41 ports across the Brazilian coastline. Proved by statistical significance, the drone-derived vessel counts revealed 17.9% and 26.6% more fishing vessels than ground- and boat-based surveys, respectively. These differences were further highlighted during the assessment of ports without a ground walkway, causing difficulty, especially for ground-based surveys. Considerable numbers and types of onboard fishing gear were detected using the drone survey, that could not be detected using the ground- and boat-based methods. Although the ground-based survey was associated with a lower cost in comparison with other methods, the drone-based survey required the least time to record fishing fleet features in study ports. Our findings demonstrate that drone surveys can improve the detection and precision of counts for fishing vessels and fishing gear in ports. Further, the magnitude of the discrepancies among the three methods highlights the need for employing drone surveys as a considerable time-reducing approach, and a cost-effective technique for fishery studies.

**Keywords:** fishing fleet; unreported data; sampling designs; drone studies; fishery management



**Citation:** Reis-Filho, J.A.; Giarrizzo, T. Drone Surveys Are More Efficient and Cost Effective Than Ground- and Boat-Based Surveys for the Inspection of Fishing Fleet at Harbors. *Coasts* **2022**, *2*, 355–368. <https://doi.org/10.3390/coasts2040018>

Academic Editors: Andrew Martin Fischer and Thomas Schlacher

Received: 20 September 2022

Accepted: 9 December 2022

Published: 16 December 2022

**Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



**Copyright:** © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

Many fishery systems lack reliable data, which serves as the cornerstone of effective fishery management [1]. These systems require data not only about events on the water, but also on fleet structure in their ports and the types of boats to be employed for different fishing techniques. Fisheries are facing a steady increase in regulatory and market demands for transparency and accountability [2]. Technological advances can help meet this demand to inform and implement science-based management and markedly improve fisheries monitoring and accountability in the coming decade [3,4]. However, the global small-scale and commercial fishery sectors lack the political will, management and legal frameworks, capacity, and compliance tools for certain enforcements [5]. According to an estimate by the World Bank, this has led to over USD 80 billion loss in annual net benefits than would be obtained if fisheries were managed in a sustainable manner [6]. Thus, improved data collection, and the ability to enforce regulations, are important starting points to address this imbalance.

In recent decades, drones, or unnamed aerial vehicles (UAVs), have proven to be effective for surveillance and inspection [7,8], especially in fishery studies [9,10]. Drones can improve data collection in field studies by facilitating the rapid survey of areas, adding aerial perspectives, and allowing access to sites previously considered inaccessible (e.g., remote, or outlying areas, high topography locations, and marine protected areas) [11], as drones can easily travel and map long distances. Drones also offer a unique and valuable perspective [12]. For example, the waterbird populations in fragile environments can be mapped efficiently and faster using drones [12]. For marine research, drones have enabled safe and cost-effective studies associated with fishery operations, for example the monitoring and surveillance of fishing practices (i.e., submerged and/or floated gear) (sensu 9). Drones have replaced the need for close-vessel approaches or vessels completely (e.g., during research on whales) [13] and have enabled research from the shore (e.g., in shark research) [14]. From the perspective of fishery studies and expected solutions, the use of drones to assess small-scale activities, such as those restricted to estuaries and/or remote locations with limited financial resources, can help maximize the effectiveness of monitoring and inspection by overcoming the lack of detection without needing more human hours [9]. Despite several challenges, such as limitations in flight time, range, and weather-dependent flying (e.g., low wind and no rain), drones still offer multiple opportunities to collect data on aspects of the fishing fleet, which would previously have been impossible. For example, in harbors or rest places, the detection and quantification of fishing vessels can be optimized using drone approaches, besides the performance of flights at lower altitude to identify fishing gear disposed on the deck, to gain a more complete picture of fleet characteristics [9,10].

Potential biases in data collection and the completeness of research outcomes will primarily be determined by the selection of the survey methods used; this is an essential aspect of successful project planning [15] and will depend on the advantages and disadvantages of each method, such that these must be properly tested [16]. Although the use of drones in fisheries research has various advantages, their use may be considered a complementary method compared with other approaches, such as landing and harbor monitoring, and onboard inspection [15]. On the other hand, high costs are associated with the implementation of these traditional approaches [17]. Thus, remote-sensing techniques are increasingly being considered as cost-effective alternatives to traditional data collection [18–22]. Despite the rapid uptake of drones by researchers, studies directly comparing the drone-derived data of fishing fleets to paired ground- and boat-based surveys, especially for small-scale and commercial fishery systems, are lacking.

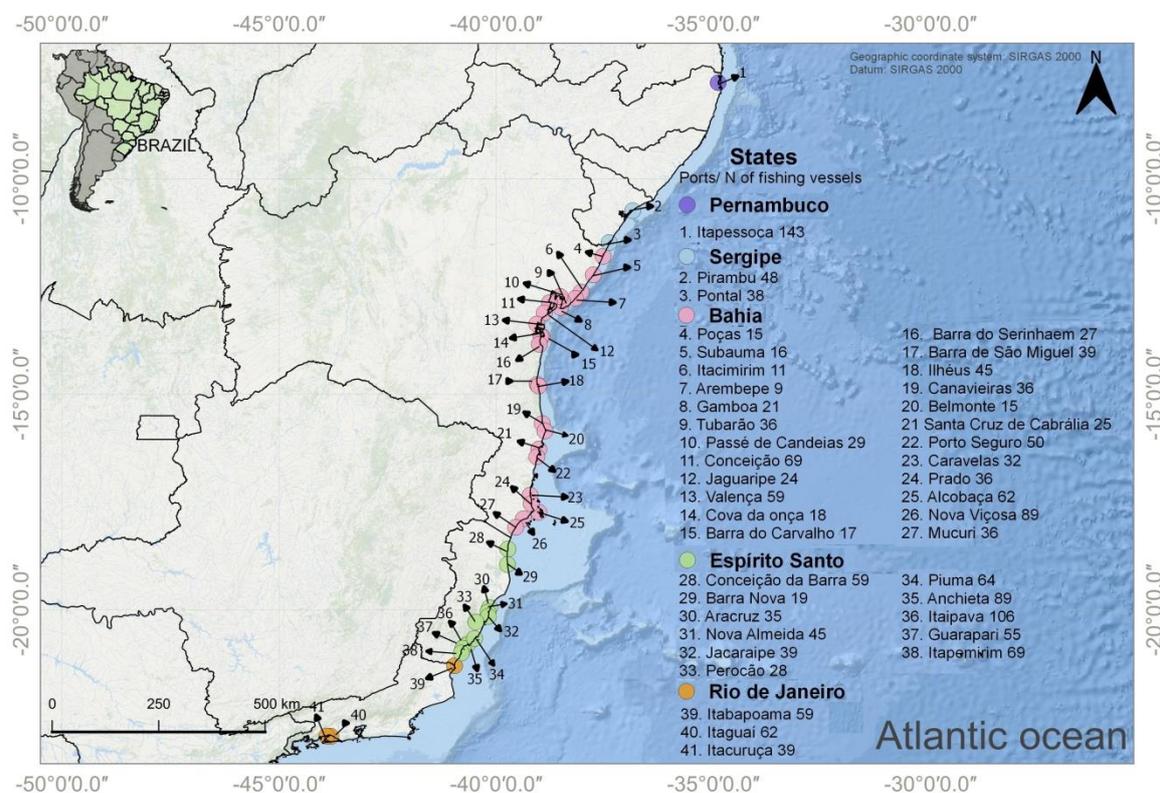
In this study, the performance of drone surveys compared to traditional surveys (i.e., land-harbor and onboard views) was evaluated to assess the cost-effectiveness of drones for the collection of fishing fleet data. The primary aim of this study was to compare survey methods (land-based observers, boat-based observers, and drone collected images) to count commercial and artisanal fishing vessels and categorize their gear in a variety of ports. We hypothesized that in-field quantification and the identification of fishing vessels and aspects of the fishing operation (i.e., number and types of fishery gear on the deck) would be improved using drone surveys. Finally, the potential of the drone approach for future inspection and the monitoring of fishing fleets, and management improvement, was revealed.

## 2. Materials and Methods

### 2.1. Study Area

The Brazilian coast, especially the eastern part, is among the most fishery productive areas in the South Atlantic Ocean. Further, the extended continental shelf comprises the largest and most biodiverse coral reef complex in the South Atlantic [23–25]. Data were collected between 2018 and 2022 in the coastal regions of Brazil (7° 45' S, 34° 50' W and 22° 56' S, 43° 47' W), which are traditional harbors for artisanal and commercial fishing fleets that catch different pelagic and demersal marine fishes and many crustacean species.

A total of 41 ports were investigated (Figure 1) and grouped into the following three types: (a) ports where the vessels are mostly docked near the shoreline; (b) ports where vessels are anchored along estuarine channels and embayments away from the ground walkway, and (c) ports where there is a combination of (a) and (b).

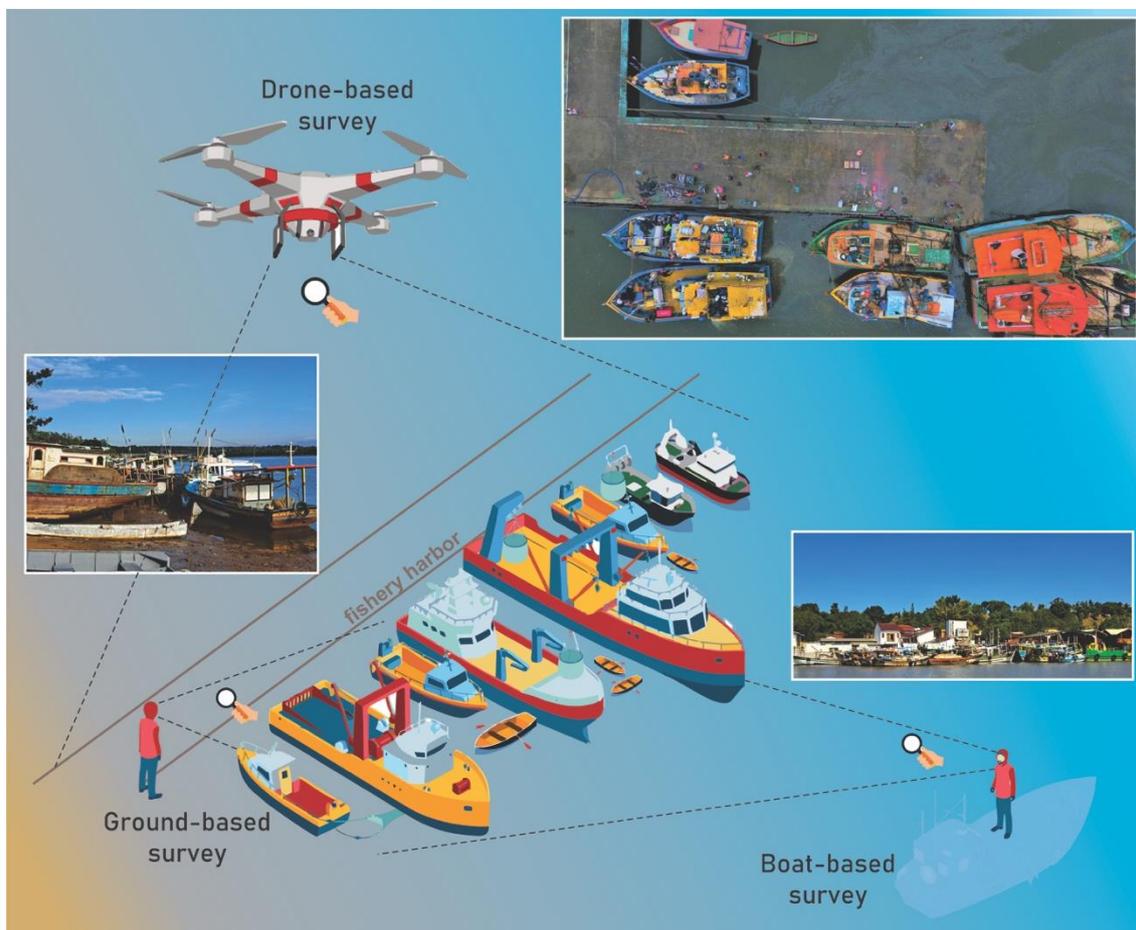


**Figure 1.** Map of the Brazilian coastline showing the surveyed ports. The number of fishing vessels recorded in each port were obtained in this study using three survey approaches (i.e., ground-, boat- and drone-based surveys). The different colors in each port represent the surveyed states in the Brazilian coast.

## 2.2. Fleet Survey Protocols

Three independent survey methods were used to estimate and characterize the fishing fleet in each of the investigated ports. The three assessment protocols were employed on the same day to avoid changes in fleet structure due to the departure and arrival of vessels. Ground and boat surveys were conducted in the same area covered by the drone flight and over the same spatial footprint, to ensure that the data was comparable. For the ground- and boat-based approaches, an observer traveled close to the vessels either by walking the port installations or shoreline for land-based surveys, or using a small boat for boat-based surveys, to collect the following data: the number of vessels employed in fishing (i.e., by identifying the presence of fishing gear on the deck), the types of gear used for the fishing activities (e.g., gillnets, trawl net gear, long line and hook and line gear, and crab traps), time spent, and the cost (USD) associated with the inspection. Along the whole study, ground- and boat-based surveys were conducted by a single observer, while drone-based surveys had a different observer. At the end of sampling, both observers also performed post hoc examination of the aerial images recorded by the drones. Briefly, each survey counted the number of fishing vessels present and the types of gear onboard each vessel. For the boat-based survey, the maximum survey speed was limited by the maritime speed zones. Recreational boats, such as sailing/motor yachts, and service vessels, were identified in situ through specific characteristics onboard, such as sails used to race and structures to carry cargo or passengers, respectively, and both were excluded from the analysis.

The drone-based surveys were conducted immediately after the ground- and boat-based surveys (Figure 2). Drone flights in all study ports were only conducted under fine conditions (i.e., no precipitation and light to moderate wind (<15 knots)). The Phantom 4 Pro (Shenzhen DJI Sciences and Technologies Ltd., max flight time 28 min per battery), with four-rotor drone (1.38 kg; diameter: 35 cm engine-to-engine) equipped with a polarized filter mounted on the built-in camera, was employed as the aircraft platform. The drone was launched and retrieved from a custom-built platform on a ground station. All flights were conducted between 15 and 50 m above water level to minimize potential disturbance and lasted between 10 and 25 min for the detection of the entire fishing fleet at a speed of  $5 \text{ m}\cdot\text{s}^{-1}$ , with the camera orientation varying from  $70^\circ$  to  $90^\circ$ . The aerial workflow to image acquisition was based on free flights (similar to procedure made by [10]) and over parallel transects to the shoreline for the recording of the entire fishing fleet at the harbor. Flight plans and ground stations were selected to ensure the coverage of the entire sample area and prevent double counting. The acquired images were used to obtain vessel counts and type, and counts of onboard fishery gear.



**Figure 2.** Schematic of the survey protocols employed on the study ports ( $n = 41$ ) to count vessels and identify fishing gear.

### 2.3. Data Analysis

Counts of the fishing vessels and counts of the fishery gear on the deck in each study port were treated as dependent variables. The performance of the three methods was analyzed using ANOVA [26] to quantify how changes in the dependent variables were associated with the survey protocols, and by calculating the coefficient of determination ( $R^2$ ) based on a regression analysis between each protocol.  $F = \text{MST} / \text{MSE}$  where  $F$  is the ANOVA coefficient, MST is the mean sum of squares due to treatments (i.e., sur-

vey methods) and MSE is the mean sum of squares due to error. The Shapiro–Wilk and Watson–Wheeler tests were used to assess the presence of normally distributed data and homogeneity in the dataset, respectively [27]. The  $p$  values from the coefficient of determination ( $R^2$ ) were tested to assess the quality of the regression fits in relation to an exponential distribution. These analyses were carried out using the *vegan* package in R (version 3.6.2) [28].

To determine the precision and coverage rate (i.e., the proportion of vessels counts that 95% confidence bounds for the estimates of the total number of vessels) estimates at the study ports, the associated counts of the fishing vessels from each survey protocol were used to obtain the coefficient of variation (CV) of sample proportion (defined as the ratio between the standard deviation of vessels counts per survey protocol and mean from total count [29]), and coverage rate taken from the sampling population belonging to different survey protocols (similar to [30]). In practice, a 90% coverage is often set as the minimum acceptable rate. Final estimates were averaged over the 1000 jackknife sampled estimates (nonparametric bootstrapping technique) which produced an expanded total of fishing vessel counts (i.e., estimation total). The precision was determined based on the mean estimates, estimated total CV, and relative standard error (RSE), respectively. The RSE was used to gauge how well the sample total aligns with the total vessel counts. In fisheries research practices, a relative standard error of 20% is often identified as an appropriate threshold [31].

The operational and fiscal cost and the time (minutes) taken to complete each survey were used to develop an estimated cost per survey for all applied protocols to evaluate their cost efficiencies (similar to [29]). For the drone-based survey, the times of the in-field and post-collection images analysis were summed to estimate the total time spent. To compute the cost of the ground- and boat-based surveys, the technician cost (USD 10.5/h) from the university operating procedure was based on the current award rates. In the boat-based surveys, the costs associated with boat supplies and rent for each surveyed port were added as standard servicing (USD 20.0/h). For the drone-based surveys, the estimated general logistic cost, including operator, payloads, battery recharging, post-processing, and license/permits when necessary, was USD 35.0/h; this value may slightly vary based on the specific flight platform and the number of flights performed [10]. The initial costs associated with drone acquisition and in-field training were not computed, suggesting that this type of research must be primarily conducted by experienced researchers.

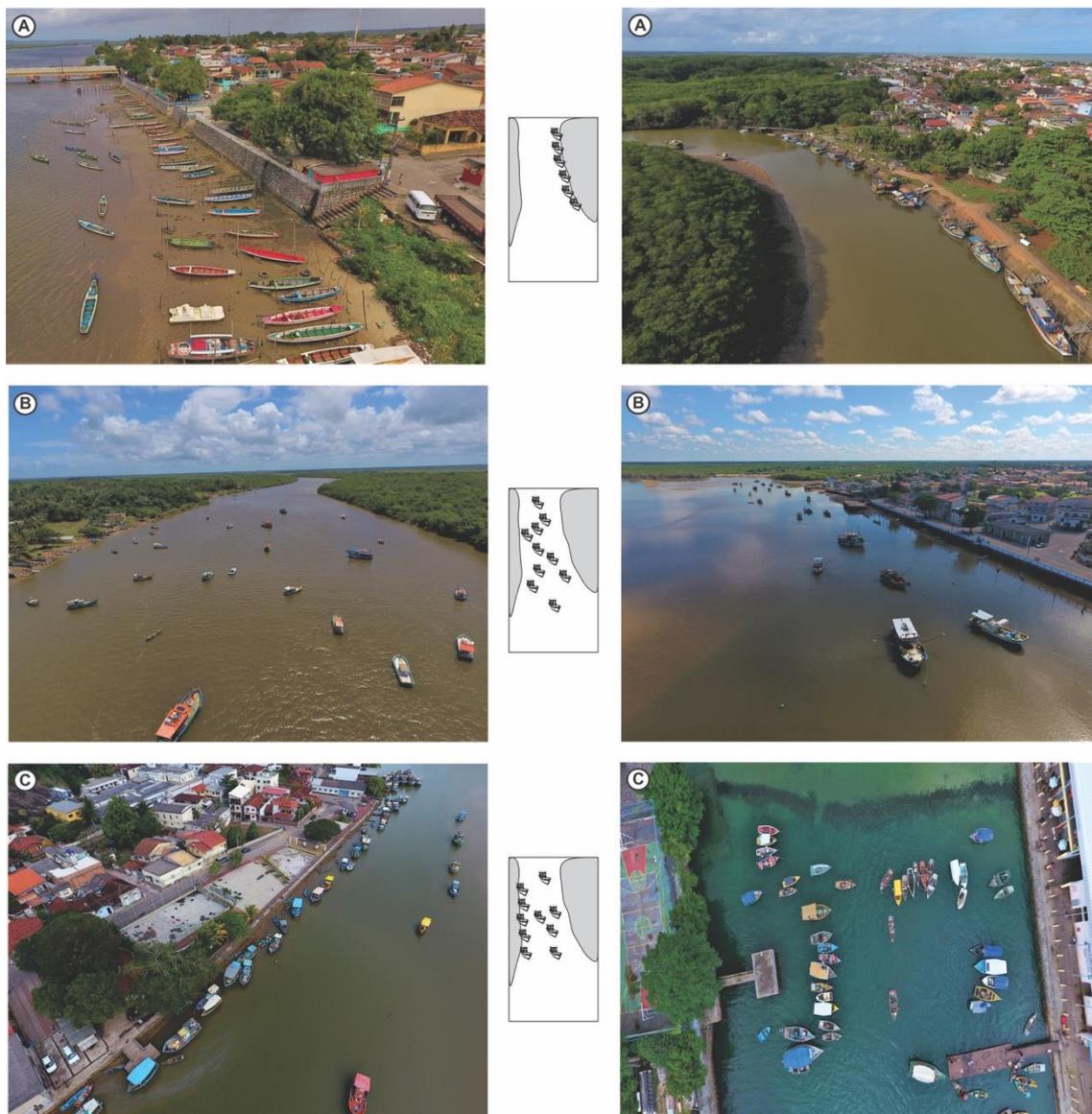
### 3. Results

#### 3.1. Relationship between the Number of Vessels and Presence of Fishing Gear Based on the Ground-, Boat-, and Drone-Based Surveys

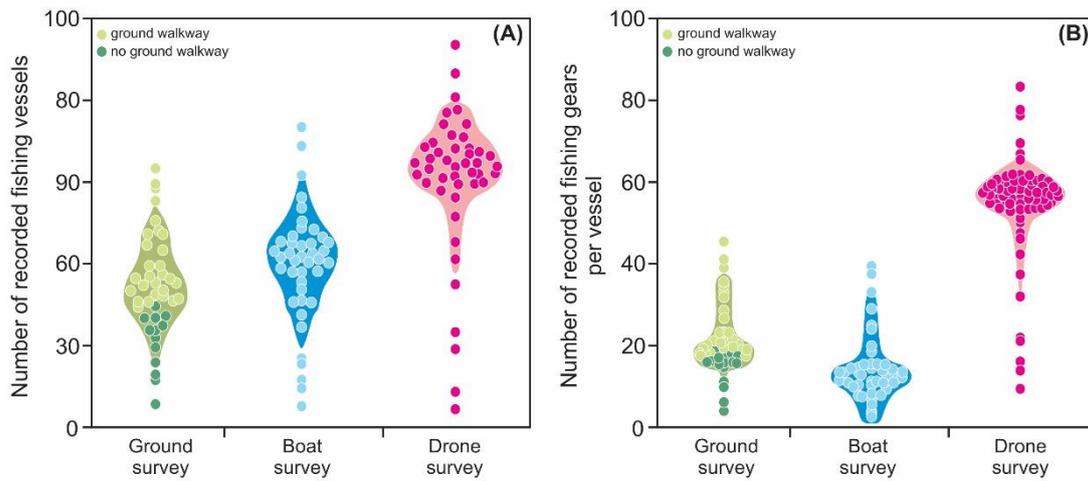
During the study, the ground-based surveys recorded 1215 vessels, the boat-based 1391 vessels and drone-based surveys recorded 1813 vessels. The number of vessels by port varied from 9 to 143, with a total across all ports of 1813 harbored fishing vessels. Accordingly, whilst one specific vessel in a given port could be recorded by all three survey protocols, it was considered as a single count per survey protocol. In all, 80.5% of the ports ( $n = 33$ ) had a ground walkway that enabled the docking of vessels close to the port. Further, 12.2% of the ports ( $n = 5$ ) had vessels docked away from the ground walkway due to anchoring along estuarine channels and/or embayments. Finally, in 7.3% of the ports ( $n = 3$ ), the vessels were randomly anchored and had also a ground walkway (Figure 3). The mean number of vessels detected during the surveys was significantly greater for drone surveys than ground and boat surveys (ANOVA;  $p < 0.002$ ; Figure 4a). This difference was even greater when ground surveys performed in rest areas lacking a port structure were separated from those performed in areas with a ground walkway (ANOVA;  $p < 0.0001$ ; Figure 4a—light and dark green circles).

A significant difference was found with regards to counts of onboard fishing gear detected on vessel decks (ANOVA;  $p < 0.001$ ), with drone surveys recording the highest counts (Figure 4b). A significant relationship existed among the number of vessels and

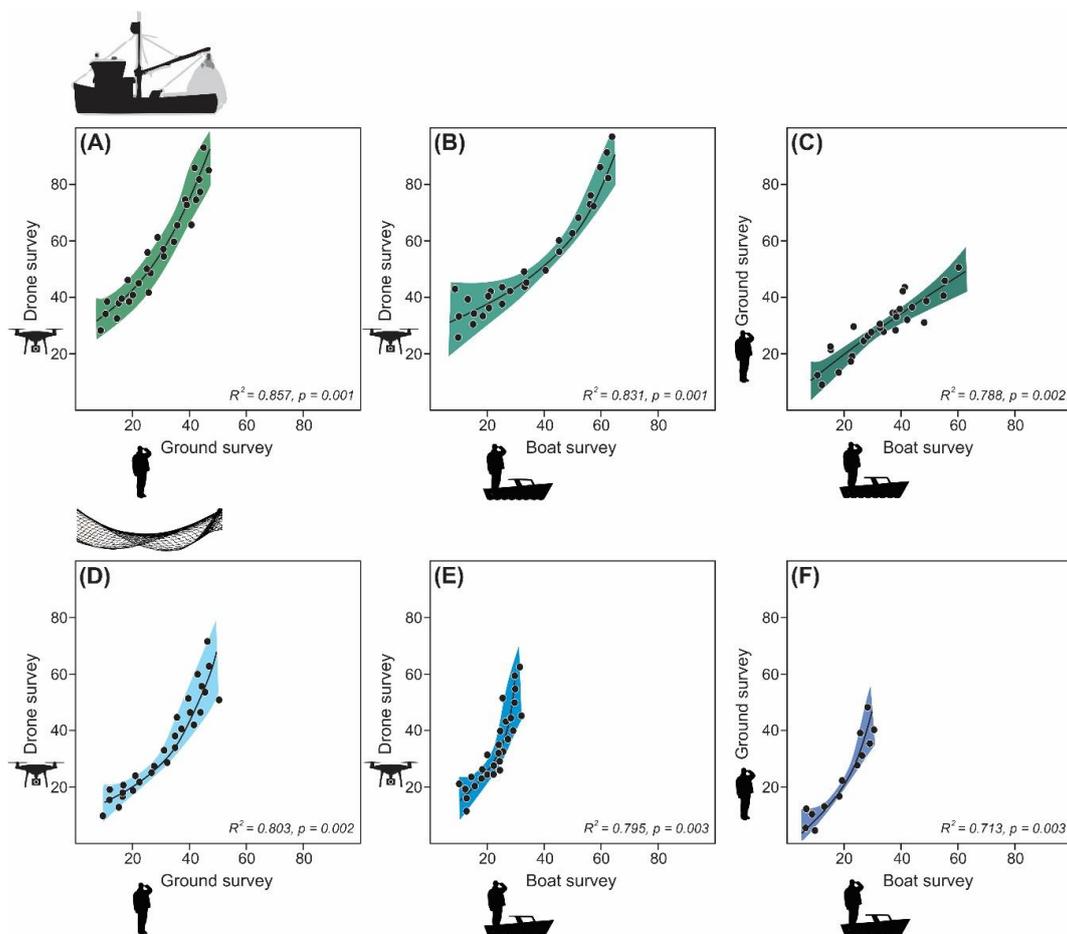
detected fishing gear identified by all protocol surveys, with drone surveys gradually increasing the likelihood of recording fishing vessels and gear (Figure 5). For vessel detection, drone surveys estimated the range of variation from an exponential relationship higher than that found using ground- and boat-based surveys (Figure 5A,B (A ( $p = 0.001$ ) and B ( $p = 0.001$ ))), as also revealed by the detection of onboard fishing gear (Figure 5D,E (D ( $p = 0.002$ ) and E ( $p = 0.003$ ))). This means that a sample from drone survey yielded higher number of vessels and fishing gear in comparison with ground and boat protocols.



**Figure 3.** Examples of common harbor configurations and vessel deployments recorded in the study ports. (A) small fishing boats employed at the gillnet fisheries and vessels used for shrimp fisheries docked near the shoreline, (B) vessels employed at gillnet, hook and line, and shrimp fisheries anchored along estuarine channels and away from the ground walkway, and (C) vessels anchored near the port and along the shoreline port area.

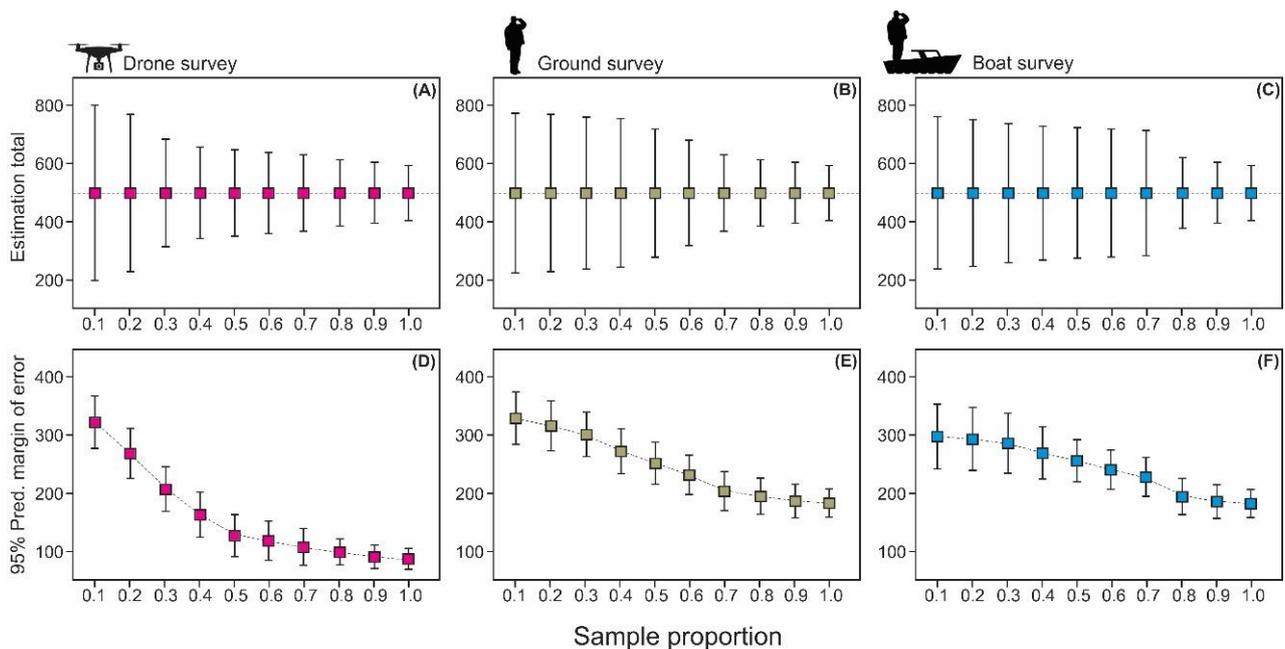


**Figure 4.** Number of fishing vessels (A) and onboard fishing gears (B) from the ground (shades in green), boat (light blue tones), and drone surveys (pink tones) at the study ports. The larger widening of the shading area in violin plots indicates greater probability of occurrence of the observed pattern.



**Figure 5.** Estimation of the relationship (coefficient of determination ( $R^2$ )) between fishing vessel counts (A–C) and onboard fishing gear (D–F) counts using drone-, ground-, and boat-based survey data. The silhouettes above the panels represent vessel and gears counts, respectively.

The confidence bounds around the predicted estimates of vessel counts considerably narrowed from 0.3 sampled proportion for the drone-based survey, indicating consistency and stability in the estimates obtained (Figure 6A). For the ground- and boat-based survey protocols, the predicted estimates of the sampled proportion was 0.6 and 0.8, respectively (Figure 6A,B). The level of uncertainty around the estimates associated with performance vessel counts (predicted margin of error) varied among the surveys; there was higher precision for estimates obtained from drone-based surveys (Figure 6D) in comparison with ground- and boat-based survey protocols, respectively (Figure 6E,F). The RSE ( $\pm$ standard deviation) obtained using the survey protocols for sampling proportions from 0.3 was below the 20% threshold for the drone-based survey, whereas those for the ground- and boat-based surveys were below 35% and 40%, respectively (Table 1). The relationship between the sampled proportion and RSE shows an exponential decay at the sampling proportion, with an improved level of precision for the drone-based survey (Figure 6D). The coverage rates for the survey protocols were within the acceptable range, regardless of the sampling proportion. However, the drone-based survey achieved over 90% coverage across the various sampling proportions (Table 1). At the 0.3 sampling proportion, the drone-based survey achieved almost full coverage. Further, the differences in coverage performance were more apparent when the drone-based survey was compared with the human-based surveys (Table 1).



**Figure 6.** Expanded total of fishing vessel counts (A) drone survey; (B) ground survey and (C) boat survey) and the 95% predicted margin of error (D) drone survey; (E) ground survey and (F) boat survey) as a function of the survey protocol based on a posteriori data analysis. Sample units were randomly selected without replacement using the different survey protocols. The results were averaged over 1000 resamples. The error bars indicate the standard error of the average of the estimates from resamples. The horizontal dashed lines represent the true point estimates based on a census of all counts from the observed data sets.

**Table 1.** Average relative standard error ( $\pm$  standard deviation) and the coverage rate from the 1000 jackknife draws for the survey protocols across the sampling proportions for fishing fleets in the study ports.

Survey Protocol	Relative Standard Error (%) Sampling Proportion									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Drone-based	28.05 $\pm$ 5.3	22.51 $\pm$ 4.7	20.14 $\pm$ 5.1	19.68 $\pm$ 4.7	17.53 $\pm$ 4.9	14.91 $\pm$ 3.3	13.95 $\pm$ 5.8	13.11 $\pm$ 2.7	12.18 $\pm$ 1.2	10.99 $\pm$ 0.8
Ground-based	45.19 $\pm$ 7.2	43.74 $\pm$ 5.1	39.44 $\pm$ 5.8	34.11 $\pm$ 5.8	32.25 $\pm$ 4.1	29.31 $\pm$ 3.8	25.83 $\pm$ 5.7	23.05 $\pm$ 3.5	22.19 $\pm$ 1.9	20.64 $\pm$ 1.1
Boat-based	48.48 $\pm$ 5.9	46.12 $\pm$ 6.1	43.58 $\pm$ 5.2	39.15 $\pm$ 4.9	38.51 $\pm$ 5.2	36.94 $\pm$ 4.4	33.13 $\pm$ 3.9	32.19 $\pm$ 4.1	29.95 $\pm$ 2.1	25.06 $\pm$ 0.9
	Coverage rate (%)									
Drone-based	91.1	93.5	93.9	96.5	96.9	97.1	97.5	98.2	98.5	98.9
Ground-based	80.3	80.9	81.5	82.1	82.6	82.7	84.3	85.2	85.5	86.2
Boat-based	75.7	76.4	77.5	79.9	80.2	80.6	81.4	81.9	82.2	82.9

### 3.2. Cost-Effectiveness Analysis of the Survey Protocols

The drone-based survey required the least time to complete the survey and analyze the images in each study port ( $31 \pm 5$  min (mean  $\pm$  SD); including field flights and post-collection image analysis) compared with the ground-based ( $89 \pm 39$  min) and boat-based ( $68 \pm 28$  min) methods. The ground-based survey was associated with a lower cost than the drone- and boat-based surveys. Accounting for general costs and technician wages, the average cost of sampling each study fishing fleet using the ground-, drone-, and boat-based surveys was USD  $18.5 \pm 4.7$ , USD  $21.4 \pm 2.7$ , and USD  $55.9 \pm 7.2$ , respectively; although these values exclude the maintenance costs for aircraft platform.

## 4. Discussion

In this study, a comprehensive analysis was performed to ultimately guide the design and resourcing of sampling for fishing fleet surveys in harbors. Vessel counts and fishing gear detection obtained using drone-based surveys were found to significantly differ from those obtained using ground- and boat-based surveys. This result supports the hypothesis that drone-based surveys identify more vessels and elements related to fishing practices than traditional methods. Although the general fishing sector poses significant livelihood source, it also contributes with a considerable amount of catch that adds to the biomass extracted from the ecosystems [32]. Besides, its magnitude is rarely accurately assessed since the size of the fishing fleet, which may be understood as a measure of fishery capacity, has been incompletely recorded or omitted from official catch statistics on a global scale [33,34]. The same situation is true for Brazilian coastal waters, in which small-scale and commercial fisheries are likely undercounted, owing to a lack of monitoring system and surveillance by the government [35,36].

Several methods have been applied to identify and estimate the fishing fleet, such as information from fishing licenses, in situ interviews, and onboard observations [9,37]; however, these methods can be inaccurate, time consuming, and expensive [34]. Therefore, alternative methods, such as the use of drone surveys, are considered reliable and could be employed as efficient, complementary or even primary methods, as previously revealed [9,10]. The results of the present study demonstrate how the detectability and precision of the estimates of the number of fishing vessels are influenced by different survey methods. Herein, a higher number of fishing vessels (1813) was recorded using the drone surveys than the traditional ground- and boat-based surveys (1215 and 1391, respectively). Further, based on direct comparisons (see Figure 4) and regression analyses (see Figure 5), an improved quantification of onboard fishing gear was obtained with the drone surveys (Figure 7). Ports in which vessels are docked away from the ground walkway prevent the successful performance of the ground-based survey; these differences were further pronounced, especially the detection of fishing gear (Figure 7A). Adapting automated procedures is critical for incorporating drone data into long-term monitoring programs, as this will reduce potential bias due to visual interpretation and provide comparable data over time.



**Figure 7.** Examples of the view obtained using each survey protocol. (A) Drone-based surveys with identification of the fishing gear; (B) ground-based survey; and (C) boat-based survey, both with limited view over the deck of the vessels.

Research on fishery fleets yields information on the possible effort and can be used to identify potential fishing pressure on stocks, especially in small-scale coastal fisheries, which is stronger in the study area [23,24]. Quantifying the number of fishing vessels is important to achieve sustainable fisheries management as fishing can substantially impact certain coastal resources [36,38]. Based on the present study, a substantial amount of vessels would be largely underestimated, when the ground- or boat-based survey is employed to assess fishing fleet. Conversely, drone surveys reveal significantly more fleet capacity than previously known, and as fishing is an integral part of the economy and the society of many coastal communities, especially in Brazil [39], inaccurate fishing vessel identification and the lack of official catch reporting [35] hinder any attempt of designing and implementing realistic and effective management plans [40].

Owing to recent advancement and affordable platforms in drone technology [41], the viability of this type of aerial survey for collecting fishing data and comparing methods for precision, data correlation, time, and costs to those of traditional ground- and boat-based methods, can be assessed. In the present study, drone surveys could collect data on fishing vessel counts and fishing gear, and were markedly less time-consuming (including post-collection analysis) than the traditional methods. Although ground-based surveys are slightly less expensive owing to their initial lower costs, this difference cannot be translated to an overall higher performance. The perspective of drone imagery can reduce the likelihood of missing fishing vessels in the study area, or missing counts due to the existence of many vessels side-by-side in ports, which might obscure the observer's line of sight (Figure 8). In addition, when ground- and boat-based estimates are employed, especially for vessels anchored close to each other, access to their decks will depend on the owner's authorization, which hampers the equal detection of fishing gear relative to that achieved with drone surveys. Drone-based counts enable the accurate performance of these inspections and are therefore useful when studying large fishing fleets. Accordingly, emerging technology enables the development of innovative methods [42]. Further, a comparison of these methods to established techniques is important to identify best practice and cost-benefit analyses when designing surveys [29]. Despite the advantages of the

drone-based option, caution must be exercised during drone flights, especially during high wind and rain. Thus, the use of drones for long-term fishery research projects may have limitations different to ground- and/or boat-based surveys.



**Figure 8.** Examples of the visual perspective of an observer using the (A) ground- and (B) boat-based survey, with potential constraints regarding vessels and fishing gears detection from the observer's point of view.

The sampling designs considered in this study are simple to understand and easy to implement in fishing fleets assessments. In the present study, although the boat-based survey has produced higher absolute vessel count than the ground-based, it was identified as the less effective protocol owing to the vessel coverage and total estimation of vessel counts. Such findings imply that the boat-based survey was the least stable survey in the jackknife draws performed. The boat-based surveys most often retrieved estimates with large variability compared to the ground- and drone-based surveys, with drone-based surveys yielding more consistent estimates and their variability decreasing in a well-defined fashion across sampling proportion. Although the sampling units (i.e., fishing vessels) had an equal probability of selection [43], the type of used survey is prone to yielding samples that are representative of a smaller sampling proportion, resulting in more variability among the sample estimates within each protocol. Based on the results obtained, the drone-based survey is a useful sampling method for evaluating fishing fleets and would yield sample estimates that are more precise, especially when there is no prior knowledge of the strata level and the data possess cyclical patterns, such as fishing fleets at a harbor [34]. Of note, the survey protocol should be used with caution, especially when deciding on the sampling moment to be used. For instance, the presence of fishing vessels in ports is influenced by whether it is fishing season, as a function of the inherent probability of a vessel being encountered in the port [44]. Notably, this study did not include fishing vessels that were at sea during the performance of the surveys or vessels kept ashore in yards and garages. However, based on empirical knowledge, previous anecdotal data, and the total capacity of all study ports, the error for the total estimate regarding vessels at sea should not exceed 10%.

## 5. Conclusions

Drones can collect high-resolution spatial data over large and inaccessible areas at an affordable cost, depending on the surface to be covered [45]. For example, this technique can be deployed at a greater distance from a ground point and for the inspection of several small fishing ports separately distributed at a harbor zone, ultimately providing a better and cost-effective perspective on local fishing fleets to better inform appropriate management measures. Furthermore, although not reported in this study, the drone imagery can be used for different post-processing analyses, such as identifying the state of conservation and dimension (i.e., size) of the vessels and fishing gear. Drone-based surveys can provide improved datasets on fishing fleet structure and thus advance our knowledge on fishery management, thereby improving efforts to minimize the time and costs of field researches.

**Author Contributions:** J.A.R.-F. conceived the research idea, designed the field study, performed the fieldwork and data collection, analyzed the data, and wrote the manuscript. T.G. wrote and revised several drafts of the manuscript. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Acknowledgments:** This research complied with the Brazilian Civil Aviation Authority (ANAC) regulations for drone operations. The authors thank the skippers and crew that participated in the boat field work and the members of the fishing communities that volunteered to assist with this project. We are also grateful to four anonymous reviewers whose comments and suggestions greatly improved the manuscript.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. FAO. *The State of World Fisheries and Aquaculture 2020; Sustainability in Action*; FAO: Rome, Italy, 2020. [CrossRef]
2. Micheli, M.; Elliott, M.; Bucher, M. *Catalyzing the Growth of Electronic Monitoring in Fisheries: Building Greater Transparency and Accountability at Sea*; California Environmental Associates: San Francisco, CA, USA; The Nature Conservancy: Arlington, VA, USA, 2018; 64p.
3. Chalkiadakis, V.; Papandroulakis, N.; Livanos, G.; Moirogiorgou, K.; Giakos, G.; Zervakis, M. Designing a small-sized autonomous underwater vehicle architecture for regular periodic fish-cage net inspection. In *Proceedings of the IEEE International Conference on Imaging Systems and Techniques*, Beijing, China, 18–20 October 2017; pp. 1–6.
4. Ubina, N.A.; Cheng, S.-C. A review of unmanned system technologies with its application to aquaculture farm monitoring and management. *Drones* **2022**, *6*, 12. [CrossRef]
5. Kura, Y.; Revenga, C.; Hoshino, E.; Mock, G. *Fishing for Answers: Making Sense of the Global Fish Crisis*; World Resources Institute: Washington, DC, USA, 2004; p. 138.
6. The World Bank. *The Sunken Billions Revisited; Progress and Challenges in Global Marine Fisheries*; World Bank Group: Washington, DC, USA, 2017; 258p.
7. Bloom, D.; Butcher, P.A.; Colefax, A.P.; Provost, E.J.; Cullis, B.R.; Kelaher, B.P. Drones detect illegal and derelict crab traps in a shallow water estuary. *Fish. Manag. Ecol.* **2019**, *26*, 311–318. [CrossRef]
8. Butcher, P.; Piddocke, T.; Colefax, A.; Hoade, B.; Peddemors, V.; Borg, L.; Cullis, B. Beach safety: Can drones provide a platform for sighting sharks? *Wild. Res.* **2019**, *46*, 701–712. [CrossRef]
9. Reis-Filho, J.A.; Giarrizzo, T. Perspectives on the use of unmanned aerial vehicles systems (UAVs) as tools for small-scale fisheries research and management. *Fisheries* **2021**, *47*, 78–89. [CrossRef]
10. Reis-Filho, J.A.; Joyeux, J.C.; Pimentel, C.R.; Teixeira, J.B.; Macieira, R.; Garla, R.C.; Mello, T.; Gasparini, J.L.; Giarrizzo, T.; Rocha, L.; et al. The challenges and opportunities of using small drones to monitor fishing activities in a marine protected area. *Fish. Manag. Ecol.* **2022**, *29*, 745–752. [CrossRef]
11. Fettermann, T.; Fiori, L.; Gillman, L.; Stockin, K.A.; Bollard, B. Drone Surveys Are More Accurate Than Boat-Based Surveys of Bottlenose Dolphins (*Tursiops truncatus*). *Drones* **2022**, *6*, 82. [CrossRef]
12. Rahman, D.A.; Sitorus, A.B.Y.; Condro, A.A. From Coastal to Montane Forest Ecosystems, Using Drones for Multi-Species Research in the Tropics. *Drones* **2022**, *6*, 6. [CrossRef]
13. Pirota, V.; Smith, A.; Ostrowski, M.; Russell, D.; Jonsen, I.; Grech, A.; Harcourt, R. An Economical Custom-Built Drone for Assessing Whale Health. *Front. Mar. Sci.* **2017**, *4*, 425. [CrossRef]
14. Tucker, J.P.; Colefax, A.P.; Santos, I.R.; Kelaher, B.P.; Pagendam, D.E.; Butcher, P.A. White shark behaviour altered by stranded whale carcasses: Insights from drones and implications for beach management. *Ocean Coast. Manag.* **2020**, *200*, 105477. [CrossRef]

15. Rahman, D.A.; Gonzalez, G.; Aulagnier, S. Benefit of camera trapping for surveying the critically endangered Bawean deer *Axis kuhlii* (Temminck, 1836). *Trop. Zool.* **2016**, *29*, 155–172. [[CrossRef](#)]
16. Buckland, S.; Magurran, A.; Green, R.; Fewster, R. Monitoring change in biodiversity through composite indices. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* **2005**, *360*, 243–254. [[CrossRef](#)] [[PubMed](#)]
17. Boenish, R.; Willard, D.; Kritzer, J.P.; Reardon, K. Fisheries monitoring: Perspectives from the United States. *Aquac. Fish.* **2020**, *5*, 131–138. [[CrossRef](#)]
18. Tyler, S.; Jensen, O.P.; Hogan, Z.; Chandra, S.; Galland, L.M.; Simmons, J. Perspectives on the application of unmanned aircraft for freshwater fisheries census. *Fisheries* **2018**, *43*, 510–516. [[CrossRef](#)]
19. Fairclough, D.V.; Brown, J.I.; Carlish, B.J.; Crisafulli, B.M.; Keay, I.S. Breathing life into fisheries stock assessments with citizen science. *Sci. Rep.* **2014**, *4*, 7249. [[CrossRef](#)] [[PubMed](#)]
20. Beckmann, C.; Tracey, S.; Murphy, J.; Moore, A.; Cleary, B.; Steer, M. *Assessing New Technologies and Techniques That Could Improve the Cost-Effectiveness and Robustness of Recreational Fishing Surveys*; FRDC Project No 2017; NOAA Fisheries: Washington, DC, USA, 2019; p. 198.
21. Ouellette, W.; Getinet, W. Remote sensing for marine spatial planning and integrated coastal areas management: Achievements, challenges, opportunities and future prospects. *Rem. Sens. Applic. Soc. Environ.* **2016**, *4*, 138–157. [[CrossRef](#)]
22. Wood, G.; Lynch, T.P.; Devine, C.; Keller, K.; Figueira, W. High resolution photo-mosaic time-series imagery for monitoring human use of an artificial reef. *Ecol. Evol.* **2016**, *6*, 6963–6968. [[CrossRef](#)]
23. Previero, M.; Gasalla, M.A. Mapping fishing grounds, resource and fleet patterns to enhance management units in data-poor fisheries: The case of snappers and groupers in the Abrolhos Bank coral-reefs (South Atlantic). *Ocean Coast Manag.* **2018**, *154*, 83–95. [[CrossRef](#)]
24. Cetra, M.; Petrere, M. Seasonal and annual cycles in marine small-scale fisheries (Ilhéus—Brazil). *Fish. Manag. Ecol.* **2014**, *21*, 244–249. [[CrossRef](#)]
25. Schmid, K.; Reis-Filho, J.A.; Loiola, M.; Harvey, E.S.; Kikuchi, R.K.P.; Giarrizzo, T. Habitat-specific fish fauna responses to different management regimes in the largest coral reef complex in the South Atlantic. *Mar. Environ. Res.* **2022**, *178*, 105661. [[CrossRef](#)]
26. Weinfurt, K.P. Repeated measures analysis: ANOVA, MANOVA, and HLM. In *Reading and Understanding MORE Multivariate Statistics*; Grimm, L.G., Yarnold, P.R., Eds.; American Psychological Association: Washington, DC, USA, 2000; pp. 317–361.
27. Zar, J.H. *Biostatistical Analysis*, 4th ed.; Prentice Hall: New Jersey, NJ, USA, 1999.
28. R Core Team. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. 2019. Available online: <https://www.r-project.org/> (accessed on 10 May 2022).
29. Provost, E.J.; Butcher, P.A.; Coleman, M.A.; Kelaher, B.P. Assessing the viability of small aerial drones to quantify recreational fishers. *Fish Manag Ecol.* **2020**, *27*, 615–621. [[CrossRef](#)]
30. Afrifa-Yamoah, E.; Taylor, S.M.; Mueller, U. Trade-off assessments between reading cost and accuracy measures for digital camera monitoring of recreational boating effort. *Fish. Res.* **2021**, *233*, 105757. [[CrossRef](#)]
31. Vølstad, J.H.; Afonso, P.S.; Baloi, A.P.; de Premegi, N.; Meisfjord, J.; Cardinale, M. Probability-based survey to monitor catch and effort in coastal small-scale fisheries. *Fish. Res.* **2014**, *151*, 39–46. [[CrossRef](#)]
32. Salas, S.; Chuenpagdee, R.; Seijo, J.C.; Charles, A. Challenges in the assessment and management of small-scale fisheries in Latin America and the Caribbean. *Fish. Res.* **2007**, *87*, 5–16. [[CrossRef](#)]
33. Pauly, D.; Zeller, D. Catch reconstructions reveal that global marine fisheries catches are higher than reported and declining. *Nat. Commun.* **2016**, *7*, 10244. [[CrossRef](#)] [[PubMed](#)]
34. Keramidas, I.; Dimarchopoulou, D.; Pardalou, A.; Tsikliras, A.C. Estimating recreational fishing fleet using satellite data in the Aegean and Ionian Seas (Mediterranean Sea). *Fish. Res.* **2018**, *208*, 1–6. [[CrossRef](#)]
35. Reis-Filho, J.A. Historical perspective of artisanal encircling gillnet use at the Brazilian coast: Changes in fishing behavior is mirrored by dwindling stocks. *Fish. Manag. Ecol.* **2020**, *3*, 1–12. [[CrossRef](#)]
36. Reis-Filho, J.A.; Miranda, R.J.; Sampaio, C.L.S.; Nunes, J.A.C.C.; Leduc, A.O.H.C. Web-based and logbook catch data of permits and pompanos by small-scale and recreational fishers: Predictable spawning aggregation and exploitation pressure. *Fish. Res.* **2021**, *243*, 106064. [[CrossRef](#)]
37. Morales-Nin, B.; Cardona-Pons, F.; Maynou, F.; Grau, A.M. How relevant are recreational fisheries? Motivation and activity of resident and tourist anglers in Majorca. *Fish. Res.* **2015**, *164*, 45–49. [[CrossRef](#)]
38. Radford, Z.; Hyder, K.; Zarauz, L.; Mugerza, E.; Ferter, K.; Pallezo, R.; Weltersbach, M.S. The impact of marine recreational fishing on key fish stocks in European waters. *PLoS ONE* **2018**, *13*, e0201666. [[CrossRef](#)]
39. Freire, K.M.F.; Almeida, Z.S.; Amador, J.R.E.T.; Aragão, J.A.; Araújo, A.R.R.; Ávila-da-Silva, A.O.; Bentes, B.; Carneiro, M.H.; Chiquieri, J.; Fernandes, C.A.F.; et al. Reconstruction of Marine Commercial Landings for the Brazilian Industrial and Artisanal Fisheries From 1950 to 2015. *Front. Mar. Sci.* **2021**, *8*, 659110. [[CrossRef](#)]
40. Lloret, J.; Font, T. A comparative analysis between recreational and artisanal fisheries in a Mediterranean coastal area. *Fish. Manag. Ecol.* **2013**, *20*, 148–160. [[CrossRef](#)]
41. Doukari, M.; Batsaris, M.; Papakonstantinou, A.; Topouzelis, K. A protocol for aerial survey in coastal areas using UAS. *Remote Sens.* **2019**, *11*, 1913. [[CrossRef](#)]
42. Bradley, D.; Merrifield, M.; Miller, K.M.; Lomonico, S.; Wilson, J.R.; Gleason, M.G. Opportunities to improve fisheries management through innovative technology and advanced data systems. *Fish Fish.* **2019**, *20*, 564–583. [[CrossRef](#)]

43. Lohr, S.L. *Sampling: Design and Analysis*, 2nd ed.; Brooks/Cole, Cengage Learning: Boston, MA, USA, 2010.
44. Desfosses, C.; Beckley, L.E. Temporal and environmental factors affecting the launching of recreational boats at entrance point boat ramp, Broome, Western Australia. In *Final Report of Project 2.1.1 of the Kimberley Marine Research Program Node of the Western Australian Marine Science Institution*; Beckley, L.E., Ed.; Western Australian Marine Science Institution: Crawley, WA, Australia, 2015; Chapter 5; pp. 77–91.
45. Linchant, J.; Lisein, J.; Semeki, J.; Lejeune, P.; Vermeulen, C. Are unmanned aircraft systems (UASs) the future of wildlife monitoring? A review of accomplishments and challenges. *Mammal. Rev.* **2015**, *45*, 239–252. [[CrossRef](#)]