Drift gillnet vessels from space: leveraging low-cost methodologies for enhanced understanding of a data-poor fishery

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Keywords
Drift gillnets | Bycatch | Pakistan tuna fishery | Indian Ocean | Satellite imagery | Tuna fisheries

I. Abstract

The Indian Ocean produces the second-highest tuna catch across the world's oceans. Here, the prevalence of drift gillnets – used to catch about one-third of tuna and tuna-like harvest – is unique compared to other global tuna fisheries, more commonly dominated by longlines and purse seines. Most drift gillnet fleets in the Indian Ocean are comprised of relatively small vessels under 24 meters in length overall. These vessels are poorly documented, fishing effort is opaque, and catch/bycatch is underreported. This is in contrast with purse seine and pelagic longline fleets operating in this region, for which fishing effort and catch are better understood and typically subject to more reporting requirements under the Indian Ocean Tuna Commission (IOTC), the regional body for managing tuna and tuna-like fisheries. Given existing data gaps and the lack of mandatory reporting to list these vessels on the IOTC Record of Authorized Vessels, this study set out to trial different approaches to better document, monitor, and understand drift gillnet fleets and, ultimately, bycatch, through satellite imagery. This study focuses on Pakistan's drift gillnet fleet as a case study. Using image annotation, deep learning on satellite images, and port-based interviews in Pakistan, we tested different methods to quantify and describe the Pakistani tuna drift gillnet fleet and bycatch. We found that several low-cost

image annotation methods and deep learning are powerful tools to illuminate information on a fleet where other monitoring and surveillance is missing. However, additional supporting information from local expertise, ground-truthing, and other considerations are necessary for robust estimates of fleet size. This paper describes 1) existing information on catch and bycatch in the Pakistani drift gillnet fleet, 2) the potential of satellite imagery analysis and deep learning towards fisheries management, and 3) the different methods, challenges, and lessons learned. This paper serves as a baseline for future similar analyses in the Indian Ocean and other regions toward a better understanding of data-poor fisheries.

II. Introduction

A. Indian Ocean fisheries and the Indian Ocean Tuna Commission

Roughly 2 billion people live along the Indian Ocean, where fisheries play important economic, cultural, and subsistence roles (Anderson, 2014; WWF, 2020). Fishing effort is increasing in the region and is significant in the context of global fisheries: the Indian Ocean accounts for almost a quarter of overall marine fisheries as of 2020 and 20 percent of world tuna catch (Karim et al., 2020; Wafar et al., 2011; FAO 2022). Catches have been increasing over the past several decades (particularly in the Eastern Indian Ocean) and reached their highest levels in 2018 at 12.3 million tons (FAO, 2020). Most catches are landed by industrial fisheries (44.4%), closely followed by artisanal (39.3%), and then subsistence fisheries (16.2%) (Palomares et al., 2021). Distant water fisheries contribute roughly three percent of total catches, primarily dominated by China, South Korea, Thailand, and Egypt (Palomares et al., 2021). Industrial fisheries catch peaked in 1997 and have declined and stabilized since then, but small-scale fisheries (including both artisanal and subsistence fisheries) have steadily increased (Palomares et al., 2021).

The Indian Ocean Tuna Commission (IOTC) is the regional fisheries management organization (RFMO) charged with managing tuna fisheries in the Indian Ocean, including drift gillnet fisheries. Established in 1993 and entered into force in 1996, the IOTC is comprised of 30 Commission Contracting Parties (Members) and two Commission Cooperating Non-Contracting Parties (CNCP) (collectively referred to as CPCs) with fishing interests in the Indian Ocean. The IOTC and its various sub-bodies, including Working Parties (i.e. the Scientific Commission, SC, and the Working Party on Ecosystems and Bycatch, WPEB), meet annually to discuss fisheries management issues in the Convention Area and provide scientific advice for the management decisions such as fishing quotas (Sinan et al., 2021).

Fishers employ a variety of gear types in the region, but gillnets are the most common and comprise over a third of nominal (e.g. reported) catches within the Indian Ocean Tuna Commission (IOTC) Area of Competence (Anderson et al., 2020; Aranda, 2017). Drift gillnets are relatively easy to set and retrieve, are cheap, and do not require bait (Anderson, 2014; Aranda, 2017). Thus, drift gillnets are an attractive fishing gear, and their use continues to expand in the Indian Ocean (Aranda, 2017; Roberson et al., 2021). Primary target species caught in these drift gillnet tuna fisheries are bigeye tuna (*Thunnus obesus*), yellowfin tuna (*Thunnus albacares*), longtail (*Thunnus tonggol*), skipjack tuna (*Katsuwonus pelamis*), kawakawa (*Euthynnus affinis*), frigate tuna (*Auxis thazard*), sailfish (*Istiophorus platypterus*), marlin

(*Makaira nigricans*, *Istiompax indica*, and *Kajikia audax*) and Spanish mackerel (*Scomberomorus commerson* and *Scomberomorus guttatus*) (Anderson, 2014; Aranda, 2017).

Under IOTC reporting requirements, most drift gillnet fisheries in the Indian Ocean are currently considered artisanal (Aranda, 2017; Kiszka et al., 2009). Almost all publicly-available data on catch from drift gillnet fleets reported are artisanal (IOTC 2023, Table 1). Broadly speaking, vessels are considered "artisanal" if they are less than 24 meters (m) in length overall (LOA) and fish exclusively within their respective exclusive economic zone (EEZ), per IOTC Resolution 19/04. Other vessels over 24m LOA and/or fishing on the high seas are considered industrial. However, the definition is not fully binary based on vessel length overall (LOA) or area of operation, as data reporting requirements vary under IOTC Resolution 15/02. The IOTC also recently developed voluntary, finer-scale reporting requirements for gillnet vessels as "artisanal," "semi-industrial," or "industrial" to work towards enhanced information on artisanal vessels in 2022 (IOTC 2022, Figure 1). Given the physical space needed on board to operate large gillnets, it is likely that many gillnet vessels in IOTC would fall into this semi-industrial category, for which data reporting remains voluntary (Aranda, 2017, IOTC 2022). Nonetheless, given the recent nature of the voluntary reporting characteristics, this study largely still refers to drift gillnet vessels as either industrial or artisanal.

Figure 1. Recent IOTC voluntary classification scheme for IOTC vessels as of 2022

Type of boat	Boat size	Area of operation	Fleet type	RAV
Non-motorised	All	Flag State EEZ only	Artisanal	No
Motorised outboard	All	Flag State EEZ only	Artisanal	No
Motorised inboard	<15 m	Flag State EEZ only	Artisanal	No
Motorised inboard	15-24 m	Flag State EEZ only	Semi-industrial	No
Motorised inboard	<15 m	Includes other EEZ areas and/or high seas	Semi-industrial	Yes
Motorised inboard	15-24 m	Includes other EEZ areas and/or high seas	Industrial	Yes
Motorised inboard	≥24 m	Anywhere	Industrial	Yes

This classification is important, as artisanal vessels, according to these definitions, are exempt from certain reporting requirements. For example, the Regional Observer Program (IOTC Resolution 11-04) does not mandate observer coverage for vessels under 24 m fishing within their EEZs; Resolution 06/03 "On Establishing a Vessel Monitoring System Programme" only requires Vessel Monitoring Systems (VMS) on vessels over 15 m fishing outside their EEZs, which excludes certain artisanal and what would be 'semi-industrial' vessels from reporting. These reporting loopholes are compounded by a lack of institutional capacity in many Member States to collect data on artisanal fisheries (Aranda, 2017).

As of April 2023, half of IOTC Members have reported drift gillnet catch for IOTC-managed fish species[1] (Table 1). From 2000-2021, the IOTC Members with the highest mean catch from gillnets were Iran, India, Indonesia, Pakistan, and Sri Lanka for both artisanal and industrial fisheries, respectively (IOTC 2022; Table 1).

Table 1: Mean catch for nations reporting drift gillnet catch for IOTC species from 2000-2021. Note: This table only refers to gillnet catch caught exclusively with "gillnets" or "offshore gillnets" in the IOTC database. Data accessed: August 2023 for nominal data last updated by the IOTC on April 11, 2023.

Fleet	Type of Drift Gillnet Fishery	Mean catch (tons)
Iran Islamic Rep.	Artisanal and Industrial	180943.54
India	Artisanal	65065.85
Indonesia	Artisanal	62690.67
Pakistan	Artisanal	56515.36
Sri Lanka	Artisanal and Industrial	29680.34
Oman	Artisanal	22318.18
Yemen	Artisanal	11984.34
Tanzania	Artisanal	5471.15
Malaysia	Artisanal	2754.48
Bangladesh	Artisanal	1752.23
Mozambique	Artisanal	959.97
Thailand	Artisanal	906.17
Kenya	Artisanal	752.53
Eritrea	Artisanal	472.05
Comoros	Artisanal	322.83
Sudan	Artisanal	50.1
Australia	Artisanal	1.63

B. Pakistan's Tuna Drift Gillnet Fishery

It is estimated that Pakistan has about one million fishers (Khan, 2011). Despite the prevalence of fishing for livelihoods, local seafood consumption is extremely low (but growing), and most catch is exported (Hornby et al., 2014). When the Pakistani fishing sector expanded after independence, the small-scale marine fishery sector consisted of local non-mechanized vessels (Hornby et al., 2014). The growth of the fisheries sector remained slow until the mid-to-late 20th century when the sector doubled due to the development of mechanized industrial fleets. Karachi harbor was the first fish landing center, and it remains the predominant landing site today, with 80 to 90 percent of the industrial fleet consisting of shrimp trawlers and larger

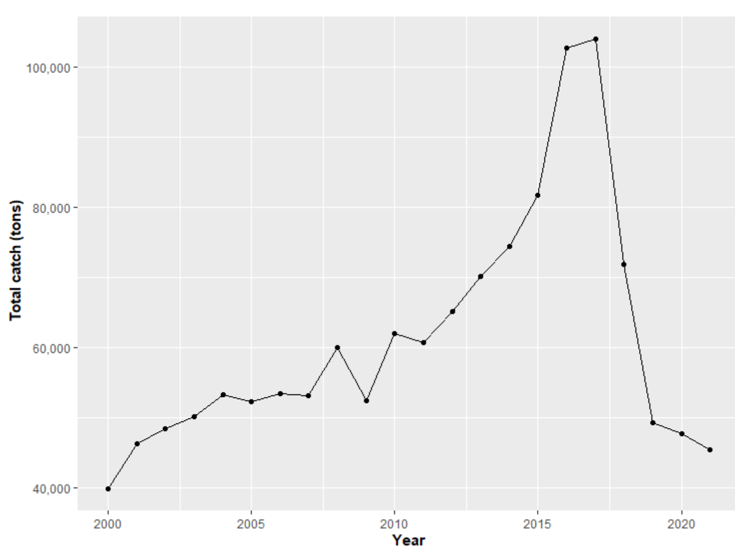
[1] The 16 IOTC-managed species are yellowfin tuna (*Thunnus albacares*), skipjack (*Katsuwonus pelamis*), bigeye tuna (*Thunnus obesus*), Albacore tuna (*Thunnus alalunga*), southern bluefin tuna (*Thunnus maccoyii*), longtail tuna (*Thunnus tonggol*), kawakawa (*Euthynnus affinis*), frigate tuna (*Auxis thazard*), bullet tuna (*Auxis rochei*), narrow barred Spanish mackerel (*Scomberomorus commerson*), Indo-Pacific king mackerel (*Scomberomorus guttatus*), blue marlin (*Makaira nigricans*), black marlin (*Makaira indica*), striped marlin (*Tetrapturus audax*), Indo-Pacific sailfish (*Istiophorus platypterus*), and swordfish (*Xiphias gladius*).

gillnetters. Pasni and Gwadar are other major sites. Shrimp trawlers, gillnetters, and longliners are the predominant industrial gears; smaller gillnets and "katra" nets (i.e., seines) also catch small pelagics (Hornby et al., 2014; Khan, 2021a). There is evidence of foreign fishing in Pakistan's EEZ, typically trawlers and longliners that operated prior to 2005 (Hornby et al., 2014).

Pakistan is the fourth-highest IOTC drift gillnet fishing nation regarding mean landed catch volume (Table 1). Gillnetting is the main fishing technique for tuna and tuna-like species in Pakistan (Khan, 2021a), and its tuna catch has been generally increasing over the past few decades until recent years (Figure 2). Pakistani gillnet fisheries landed an average yearly catch of 65,616 tons of tuna and tuna-like fishes in recent years (2015-2021) (IOTC 2023), though catches started declining in 2018 due to early closures, low catch, and warmer sea surface temperatures and jellyfish blooms (Khan, 2021b). From 2015 to 2021, Pakistan landed the highest catch of the following six respective IOTC-managed species: yellowfin tuna (25.5 percent of total catch), narrow-barred Spanish mackerel (23.3 percent), longtail tuna (19.8 percent), frigate tuna (17.5), kawakaea (5.47 percent), and then Indo-acific sailfish (3.08 percent) (IOTC 2023). It is important to note that it is likely that Pakistan's gillnet catches are underreported, as issues with catch data have been reported dating back to the late 1980s (Anderson et al., 2020; IOTC 2019a). The IOTC has reconstructed Pakistan's catch data, which are represented here (Figure 2).

The best information suggests that, as of 2017, roughly 700 pelagic tuna drift gillnet vessels operated in Pakistan, including 700 large tuna gillnet vessels between 15-25m LOA that catch tuna and tuna-like species and 1,500 smaller vessels (10-15m) operating in coastal waters, catching neritic tunas (Khan, 2018; IOTC, 2019b). No Pakistani fishing vessel, including gillnets, is currently on the IOTC Record of Authorised Vessels, which should include all vessels of IOTC Members over 24 min length or those under 24 meters and fishing outside the respective EEZ (IOTC 2022b).

Figure 2: Total Pakistani catch in tons/year in gillnet fisheries reported to the IOTC for the 16 IOTC-managed species from 2000-2021. Data accessed: August 2023; last IOTC update April 2023.



In the Pakistani fleet, drift gillnets are typically set in the evening and hauled in the morning, with an average soak time of 12 hours (Moazzam & Khan, 2018; Nawaz & Moazzam, 2014). Most tuna vessels can stay offshore lasting about three weeks, whereas the coastal tuna fleet operates for a few days at a time. The fishing fleet for large pelagic fish is concentrated in four ports: Karachi, Gwadar, Pasni, and Jiwani, but decreasingly less in Pasni (Khan, 2018; Nawaz & Moazzam, 2014). Nawaz and Moazzam (2019) report that most of the larger vessels are in Karachi, and smaller vessels are in the coastal areas of Balochistan (which includes Gwadar, Pasni, and Jiwani). No tuna fishing occurs during the monsoon months (June and July), and this pause in fishing can sometimes extend into April, May, and August due to religious holidays and other operational reasons (Moazzam & Khan, 2018).

Estimates of the length of drift gillnets used by Pakistani fishermen vary but generally range from 5 km to 11 km, with a few net lengths around 20 km (Khan 2018). Gillnets are predominantly polyamide with stretched mesh sizes from 13 cm to 17 cm with a hanging ratio of 0.5 cm (Nawaz & Moazzam, 2014). The IOTC reports that Pakistan vessel operators increased net lengths in the late 1990s (IOTC, 2019). Depending on their fishing area, this information means that some vessels are violating UN Resolution 46/215 and IOTC Resolution 12/12 banning drift gillnets over 2.5 km on the high seas (the IOTC passed Resolution 17/07 banning nets over 2.5 km used within EEZs in 2017, but Pakistan objected to this and is held to 12/12) (WWF, 2020).

Despite dedicated efforts by WWF Pakistan to monitor this fishery, significant knowledge gaps remain regarding Pakistani drift gillnet fisheries, including accurate catch statistics, bycatch trends, and spatiotemporal patterns in fishing (IOTC, 2019; Khan, 2018). In general, Pakistan's vessel registration system and estimates of the number of active vessels are considered to be unreliable (IOTC, 2019). Other issues, including double vessel registration in Pakistan and Iran (Global Fishing Watch and Trygg Mat Tracking, 2020) and vessels used to transport fish but not actively fishing, make it challenging to quantify Pakistan's gillnet fleet (Khan, 2018). A few vessels also switch their gear, transitioning between gillnets and trawls depending on the season (WWF Pakistan, personal communication, 2022).

C. Cetacean bycatch

In addition to widespread data gaps on catch statistics and fishing effort that are important for fisheries management under the IOTC, tuna drift gillnets are thought to cause very high bycatch. For marine mammals, coarse estimates find that roughly 4 million cetaceans have been killed in total in these fisheries since 1950 (Anderson et al., 2020). Estimates of cetacean bycatch in Pakistani gillnet fisheries suggest that 12,000 cetaceans are taken annually as bycatch in surface gillnets (Moazzam, 2019, 2021) whereas it was recorded to be 8,411 (SE=1,057) by Kiszka et al. (2021); Anderson et al., 2020 estimated bycatch of 8,000 to 10,000 individuals per year for Pakistan, supporting the estimate of Moazzam, 2019, 2021 and Kiszka et al., 2021.

During drift gillnet mitigation trials from 2013-2017, the species caught included: spinner dolphins (*Stenella longirostris*, n = 30, 67%), common bottlenose dolphins (*Tursiops truncatus*, n = 5, 11%), Indo-Pacific common dolphins (*Delphinus delphis tropicalis*, n = 4, 8%), Risso's dolphins (*Grampus griseus*, n = 2, 5%), pantropical spotted dolphins (*Stenella attenuata*, n = 1, 3%), dwarf sperm whales (*Kogia sima*, n = 1, 3%) and Omura's whales (*Balaenoptera omurai*, n = 1, 3%) (Kiszka et al., 2021). Other species have recently been confirmed as bycatch species, including striped dolphins (*Stenella coeruleoalba*) and Longman's beaked whales (*Indopacetus pacificus*) (Kiani et al., 2021).

In addition to the species observed in Kiszka et al., 2021, approximately 24 marine mammal species occur in the Arabian Sea (Table 2) (Notarbartolo di Sciara et al., 2021; Kiani et al., 2021; IOTC 2022).

Table 2: Marine mammal species of the Arabian Sea

Species	**IUCN Red List Status**	**Known occurrence in Pakistan***
Balaenopteridae		
Bryde's whale (*Balaenoptera edeni)*	Least Concern	Yes
Blue whale *(Balaenoptera musculus)*	Endangered	Yes
Humpback whale (Arabian Sea population) (*Megaptera novaengliae)*	Endangered	Yes
Omura's whale (*Balaenoptera omurai)*	Data Deficient	Yes
Physeteridae		
Sperm whale *(Physeter macrocephalus)*	Vulnerable	Yes
Kogiidae		
Dwarf sperm whale (*Kogia sima)*	Least Concern	Yes
Pygmy sperm whale (*Kogia breviceps)*	Least Concern	Yes
Ziphiidae		
Cuvier's beaked whale (*Ziphius cavirostris)*	Least Concern	Yes
Longman's beaked whales (*Indopacetus pacificus*)	Least Concern	Yes
Delphinidae		
Pygmy killer whale (*Feresa attenuata)*	Least Concern	
Short-finned pilot whale (*Globicephala macrorhynchus)*	Least Concern	
Risso's dolphin (*Grampus griseus)*	Least Concern	Yes

Killer whale (*Orcinus orca)*	Data Deficient	Yes
Melon-headed whale (*Peponocephala electra)*	Least Concern	
False killer whale (*Pseudorca crassidens)*	Near Threatened	
Indian Ocean humpback dolphin (*Sousa plumbea)*	Endangered	Yes
Indo-Pacific common dolphin (*Delphinus delphis tropicalis)*	Data Deficient	Yes
Pantropical spotted dolphin (*Stenella attenuata)*	Least Concern	Yes
Striped dolphin (*Stenella coeruleoalba)*	Least Concern	Yes
Spinner dolphin (*Stenella longirostris)*	Least Concern	Yes
Rough-toothed dolphin (*Steno bredanensis)*	Least Concern	Yes
Indo-Pacific bottlenose dolphin (*Tursiops aduncus)*	Near Threatened	Yes
Common bottlenose dolphin (*Tursiops truncatus)*	Least Concern	Yes
Phocoenidae		
Indo-Pacific finless porpoise (*Neophocaena phocaenoides)*	Vulnerable	Yes
Dugongidae		
Dugong (*Dugong dugong)*	Vulnerable	No authentic record

WWF Pakistan's drift gillnet mitigation efforts represent the most comprehensive bycatch monitoring program known in the Indian Ocean and provides important insight into Pakistani fleet characterization and bycatch (Moazzam 2019, 2021; Kiszka et al., 2021). Still, as is the case with all Arabian Sea fleets, information about fishing effort, catch, and bycatch is sparse.

D. *Conservation Technology for Fisheries Monitoring*

Current techniques to assess and manage fishing effort include monitoring via logbooks, onboard observers, fisher interviews, post-trip sampling, and, more recently, automatic ship identification systems (AIS), vessel monitoring systems (VMS), and remote electronic monitoring (Ewell et al., 2020; McCauley et al., 2016; Suuronen & Gilman, 2020). However, these tools, except AIS, are not always available, particularly in artisanal fleets.

Another conservation technology, namely very high resolution (VHR) satellite-based remote sensing, and its applications to marine fisheries is a relatively nascent but rapidly growing field (Toonen and Bush, 2020). Satellite remote sensing offers another promising tool to illuminate fishing activity and fill gaps in monitoring and managing vessels without VMS, AIS, or traditional monitoring systems (Corbane et al., 2010; Exeter et al., 2021; Kourti et al., 2005). It can also be used to provide environmental data that can be overlaid to better understand fisheries distributions, predator-prey relationships, marine megafauna distribution (Corbane et al., 2010; Höschle et al., 2021), and inform ecosystem-based fisheries management (Chassot et al., 2011).

Currently, three types of satellite imagery sources are typically used in fisheries monitoring: 1) Visible light, using the Visible Infrared Imaging Radiometer Suite (VIIRS), a polar-orbiting satellite that can detect vessels at night using lights; 2) Synthetic Aperture Radar (SAR), an active technology that can penetrate cloud coverage; and 3) Optical imagery, including very high-resolution (VHR) satellites, which offer a sub-meter spatial resolution, visible colors, and offers the best imagery for the purposes of object detection (Corbane et al., 2010; Global Fishing Watch, 2021; Höschle et al., 2021). A growing body of literature highlights the potential applications of these image sources to fisheries, such as using VIIRS imagery to estimate landings of a small-scale fishery in Myanmar (Exeter et al., 2021); a combination of VIIRS, SAR, VHR, and AIS to detect illegal fishing by China and North Korea (Park et al., 2020); testing SAR imagery, alongside AIS and VMS, to examine adherence to fishery closures in an MPA (Rowlands et al., 2019), and other fisheries and ecologically related applications of satellite imagery (Elvidge et al., 2018; Hsu et al., 2019; Khan et al., 2023).

For optical VHR imagery, the WorldView-3 and 4 satellites offer the highest spatial resolution that is commercially available at 0.31 m, followed by the WorldView-2 satellite at 0.46 m and Planet's SkySat at 0.50m (Höschle et al., 2021), although WorldView-4 has not been tasking since its instrument failure in 2019 (Khan et al., 2023). Access to these images can be costly (Höschle et al., 2021), but certain sources provide imagery free of charge or at discounted rates for some user groups, such as through the European Space Agency and U.S. National Aeronautics and Space Administration. Additionally, Google Earth Pro offers free and readily accessible imagery for use. These detailed images, complemented by deep learning algorithms for automated detection of vessels, are promising applications of VHR satellites in helping to fill information gaps about fisheries (Al-Abdulrazzak & Pauly, 2014; Toonen & Bush, 2020).

Computer vision, particularly deep learning, and convolutional neural networks allows the expansion of ecological monitoring at spatiotemporal scales previously too difficult, expansive, or otherwise challenging to monitor (Weinstein, 2015; Pimm et al., 2015). Deep learning is a powerful and rapidly expanding field used within many aspects of modern technology, from facial recognition to consumer advertising (LuCun et al., 2015). Within the general field, *deep learning* allows for, in brief, input of raw data into a model, machine recognition of specific patterns (e.g., pixels, shape), and an output prediction of objects based on annotation classes present in the training dataset (LuCun et al., 2015; Weinsein, 2018). Here, we were interested in testing deep learning models to detect gillnet vessels and compare those detections to manual counts. While no known studies exist that directly couple VHR imagery and machine learning with bycatch, a growing number of studies are relying on machine learning to detect whales at sea or better understand fishing effort (Cubaynes et al., 2019; Khan et al., 2023; Table 3). Combining these methods towards bycatch monitoring may be achievable in the coming years.

Table 3. Example of other studies, the type of satellite imagery, and respective study-specifics.

Paper	Manual or automated detection	Object sample size	Data source[2]	Program used for annotation	Classification category
Exeter et al. 2021	Automated	500,000 boat detections	VIIRS	ArcGIS	n/a
Rowlands et al. 2019	Manual	n/a	SAR	OceanMind	High, medium, low
Dickens et al. 2021	Manual[3]	200	Drone imagery	Dotdotgoose	cows, bulls, suckling pups and weaned pups
Moxley et al., 2017[4],[5]	Manual	435.9 mean count in an image	Google Earth	Loggerpro	n/a – count data
Keramidas, I., et al.	Manual	~500 boats	Google Earth and ground truthing	N/A – Google Earth	n/a
Cubaynes et al. 2019	Manual	4 species	WV3	ArcGIS Pro	Definite, probable, possible
Cubaynes et al., 2022	Manual	633	Digital Globe	ArcGIS Pro	Definite, probably, possible

E. *Study objectives and purpose*

This study uses satellite imagery and deep learning to test the rapidly expanding methods of VHR analysis and computer vision towards better characterizing a poorly documented fleet. We selected Pakistan as a case study given the ongoing and dedicated monitoring of the gillnet fleet by WWF Pakistan, which has provided a wealth of information to supplement our satellite analysis (Kiszka et al., 2021; Khan 2021a, b; Moazzam 2019, 2021). Our specific objectives were to: 1) characterize the Pakistani tuna drift gillnet fleet using VHR satellite imagery, coupled with ground-truthing and machine learning; 2) assess the feasibility of using VHR satellite imagery and other earth observation data to monitor the distribution of tuna drift gillnet vessels; 3) compare fleet estimates across different satellite imagery sources; and 4) develop a transparent and transferable mixed-methods approach to obtain bycatch estimates in data-poor fisheries. We

[2] Data sources include drone campaigns, single satellite platforms, or multiple platforms grouped by sensory type, data portal, or commercial provider.

[3] Note: had a second analyst verify detections in DotDotGoose

[4] Had multiple observers verify data

[5] For later analysis, includes a useful approach to missing sample bias

present preliminary results, noting that additional analyses are ongoing for this system, such as machine learning, calculation of model error, and ground-truthing components.

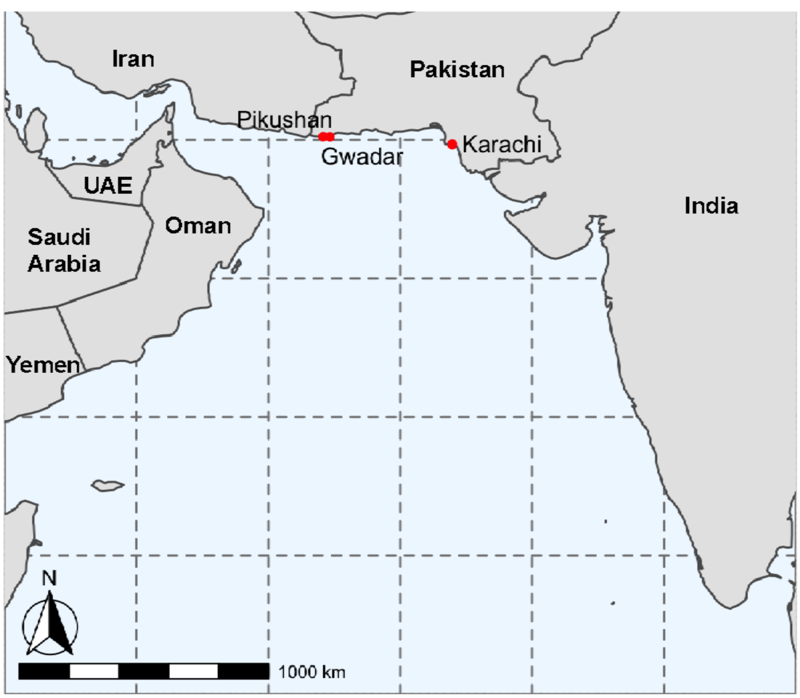
III. Materials and Methods

In this study, we tested several methods to better understand the Pakistani drift gillnet fleet, some of which represent ongoing efforts. These include: 1) Manually counting vessels using freely available and easily accessible satellite imagery from Google Earth Pro; 2) Developing and running deep learning models to count and classify vessels in this freely available imagery; 3) Training and testing deep learning models on WorldView-3 satellite imagery, and 4) Conducting port-based interviews with fishers in Pakistan. We employed the first three methods to inform estimates of fleet size and the latter to inform bycatch estimates. We discuss the general methodologies of each of these approaches below.

A. Study Sites

Importantly, this study relies on data from ports rather than vessels monitored at sea. As a preliminary application of these methods, focusing on ports allowed us to generate counts and abundant training data for classification algorithms from a relatively small number of satellite images featuring dense abundances of vessels. We also found that specifically focusing on ports was a manageable approach to the work, rather than attempting to count and classify vessels at sea. Thus, we selected three major fishing harbors in Pakistan as our ‘study sites’ for obtaining satellite imagery to analyze the drift gillnet fleet: Karachi, Gwadar, and Pishukan (Figure 3). We selected specific polygon areas of interest (AOIs) within the ports to review for analysis based on consultation with WWF Pakistan over where gillnet vessels dock with the highest density in the ports. Altogether, we reviewed six AOIs: three in Karachi, one in Gwadar, and two in Pishukan.

Figure 3. Location of three port study sites in Pakistan.



B. Google Earth Pro analysis

a. Satellite imagery access and data preparation

Google Earth Pro is a free, desktop-based application that offers users access to an archived library of global satellite coverage. It creates mosaics of processed satellite imagery from different sensors and companies (e.g. Airbus, Maxar, TerraMetrics, Landsat, and others), which users can download at certain "eye altitudes" for analysis or analyze in the desktop application. Google Earth Pro has been used in several ecological and fisheries studies to date (e.g. Moxley et al., 2017; Kapoor et al., 2023;Nijamir et al., 2023).

We reviewed all publicly available satellite imagery from Google Earth Pro for a study period of January 2021 to December 2022 ("the study period") available for the three ports at 700-750 feet eye altitude above sea level as of January 25, 2023 ("eye altitude" represents how far the user views area of interest in Google Earth Pro's digital model/digital reference level). Image availability varied by port, and we sampled all available imagery in each location for the study period. Pishukan only had one month of imagery at such eye altitude available in the study period, so we consequently extended the study period for Pishukan to the second-most recently available imagery (July 2018) – which provided one extra date of imagery.

We used Google Earth Pro's "save image" feature and downloaded imagery at the highest resolution available as *.jpg* (8192x5452 pixels) for each AOI. For each AOI, we manually tiled the region into smaller tiles in Google Earth Pro using the "add polygon" feature at 700-750 feet eye altitude. For each AOI polygon, we moved from left to right and top to down to sample imagery for the entire polygon. It was impossible to align the same eye altitude for each location, hence the flexibility to sample between 700-750 feet based on how far the analyst could zoom in per location. Analysts saved all images on a desktop and cloud-based storage system, systematically labeled with the location, image date (month and year), and polygon label (e.g. *"Karachi_Cluster2.2_10.22"*), and also recorded in a master image directory spreadsheet that also noted the eye altitude of the image.

b. Manual imagery annotation and analysis

Data annotation is a key component of computer vision. It refers to labeling objects of interest in an image (OOI) and assigning classes to objects, which are then typically fed into classification algorithms such as deep learning models (Khan et al., 2023). There is an expanding list of software tools available for image annotation, reflecting the growth of deep learning models and applications (Weinstein, 2018; Khan et al., 2023). We tested five software applications that can be used for image annotation: VGG Image Annotator, DotDotGoose, BIIGLE 2.0, CVAT, and QGIS (see the Discussion section for more information on these programs). We considered the annotation feature (e.g. box, circle), georeferencing capabilities, file storage, and other factors in software selection. We selected BIIGLE 2.0 as our image annotation software, an open-source web-based platform built for detecting OOI in the marine environment primarily for the ability to rotate bounding boxes (Langenkämper et al., 2017). We used rectangular bounding boxes to manually annotate vessels. We manually rotated bounding boxes to approximate the best fit around each vessel, as is enabled in the BIIGLE interface, which was critical given the density and positioning of vessels.

To manually count gillnet vessels in our study, we loaded each Google Earth Pro image into BIIGLE. We annotated every vessel in every image. If there was an overlap of a vessel between two images, we took two approaches: (1) For areas 1 and 2 in Karachi: researchers assigned vessels to be counted in the northern (top) polygon; (2) all other polygons: analysts counted vessels if it is more than 50 percent visible in the image.

We selected three classes for annotated vessels: “yes,” “maybe,” and “no,” based on visual characteristics of the vessel (Table 4, Figure 3, 4). A vessel labeled as “yes” indicated that the analyst detected it to be a gillnet vessel; “maybe” referred to vessels that had the shape and other defining features of a tuna drift gillnet but could not definitively distinguish it as a gillnet vessel due to image quality or similarity to other gear (e.g. trawls); and “no” referred to vessels there were definitely not gillnet vessels, such as katra vessels or water supply vessels. WWF Pakistan trained an analyst to identify gillnet and other vessels in Pakistan. Table 4 outlines the defining features of each image annotation category.

The first analyst manually annotated all images (n=832) and then a second analyst annotated a subset of images (n=213) (note: results forthcoming for the latter). Quality assurance of annotations was a two-part process: 1) after finishing annotating an image, the analyst reviewed each image and annotation before exporting into a CSV file to ensure analysts had annotated all vessels , and 2) a random sampling of annotations of each Port was reviewed with experts from WWF Pakistan. Images were systematically reviewed and corrected pending consultation with WWF Pakistan.

Table 4. Criteria for three annotation classes.

<table>
<tr><th>Annotation category</th><th>Required criteria</th><th>Additional guiding criteria</th></tr>
<tr><td rowspan="5">Yes</td><td>Flat stern</td><td rowspan="5">Space between deck house and front of vessel elevated (Karachi)</td></tr>
<tr><td>Pointed bow</td></tr>
<tr><td>Awning and/or deckhouse located at center/top center of vessel</td></tr>
<tr><td>Open space between deck house and front of vessel</td></tr>
<tr><td>Vessel not one color</td></tr>
<tr><td rowspan="3">Maybe</td><td>Flat stern</td><td rowspan="3">Image may be blurry, unclear, or the vessel may have other criteria making it hard to identify; image may have cranes or other criteria indicating it may be a trawl vessel</td></tr>
<tr><td>Pointed bow</td></tr>
<tr><td>Deck house</td></tr>
<tr><td rowspan="2">No</td><td>Submerged, partially or fully</td><td rowspan="2"></td></tr>
<tr><td>Pointed bow and stern or flat bow and stern</td></tr>
</table>

	Definitively other types of vessels: katra, trawl, or other	
	Painted fully blue or red	

Figure 3. Examples of annotated vessels in each class in BIIGLE 2.0 (mixed AOIs and time series)

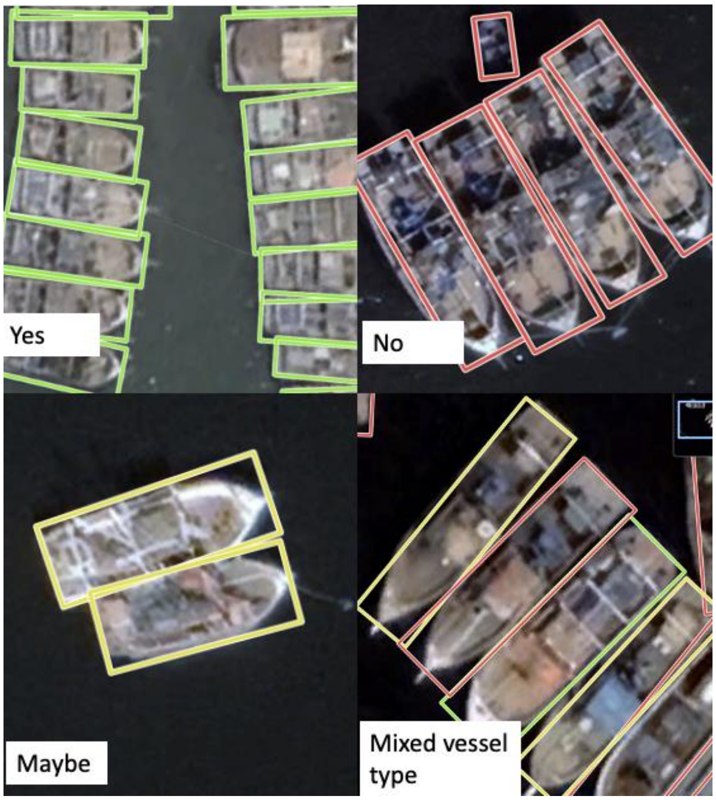
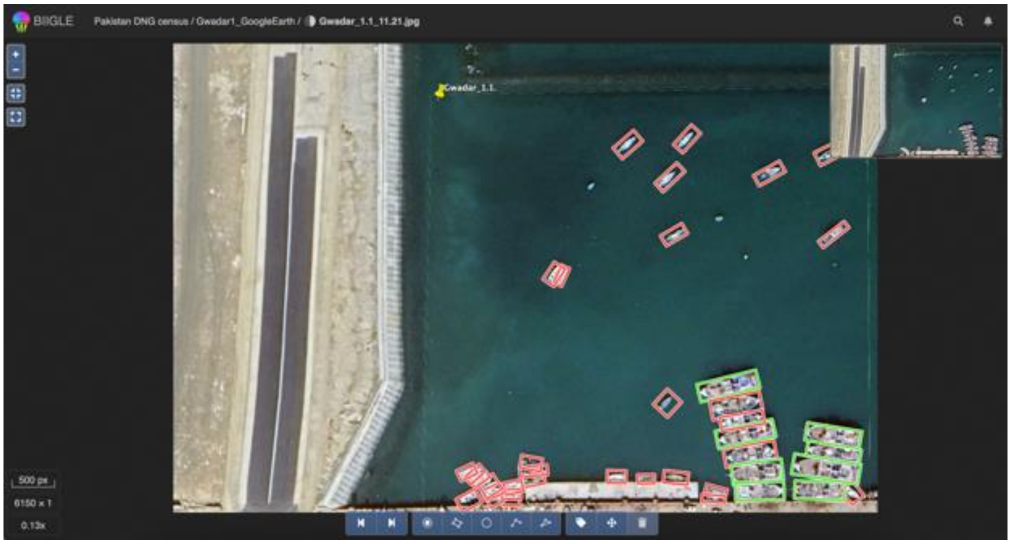


Figure 4. Example of image annotation in BIIGLE 2.0 (Gwadar, November 2021, Google Earth Pro)



c. Google Earth Pro imagery coverage

We reviewed a total of 832 images from Google Earth Pro from January 2021 through December 2022 of the ports of Karachi, Gwadar, and Pishukan at 700-750 feet eye altitude. The most imagery was available for Gwadar, followed by Karachi, and then Pishukan, which only had one image available at 700-750 feet of elevation during the study period (Table 5). In general, December/January and June through October had the lowest image availability. Karachi had the largest spatial area sampled (2.36 km^2), followed by Pishukan (1.35 km^2), and lastly Gwadar (0.18 km^2).

Table 5. Google Earth Pro image availability from January 2021 to December 2022 as of January 15, 2023.

Port	**Year**	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**	**Total months**
Gwadar	2021		xx xx	xx x	x	x			x	x		xx x		7
	2022	x	x	xx	x	x	x		x		x	x	x	10
Karachi	2021	x	x	x		x	x			x	x			7
	2022		x	x	x	x	x				x			6
Pishukan	2022			x										1
	2018							x						1

d. Manual Google Earth Pro data analysis

Once researchers annotated all the vessels, the data were exported from BIIGLE 2.0 as CSV files for each polygon for analysis in R Studio, version 2023.03.1+446. To estimate the number of gillnet vessels, we calculated summary statistics of the number of vessels over the entire study period by port, annotation class, and time; we also calculated a sample of the average vessel length for a sample of "yes" vessels (n = 75) in Karachi, Gwadar, and Pishukan by using Google Earth Pro's ruler tool[6], which is relevant for management and data reporting under the IOTC.

We initially summarized the number of vessels in three different ways by port, class, and year: 1) total annotations, 2) average annotations, and 3) the total annotations just inclusive of the months of April and May for both years — the months with highest expected boat density in ports due to weather and the closed fishing season (Moazzam and Khan, 2018). For approach 1 and 2, we note that, for Gwadar, several months yielded multiple usable satellite images per month (February, March, and November). For those months, we first averaged the total vessels for repeat imagery within a month (as to not overcount repeated vessels in the images) and used that monthly average as the overall count data for Gwadar for the subsequent analysis. For approach number 3 (April and May only annotations), Pishukan did not have any images in these months, instead just in March 2022, so we used March 2022 as the month to count boats for Pishukan.

In this paper, we share the total counts but focus on vessel counts for April and May (and March for Pishukan) as the most realistic temporal portrayal of the fleet. This procedure avoids double counting vessels from image to image, and it also allows researchers to count vessels during a. peak vessel density in port and b. avoid imagery during the monsoon season.

e. Deep Learning for Google Earth Pro Analysis

We fine-tuned a pre-trained deep learning model on a subset of Google Earth Pro images. We exported the manual annotations in BIIGLE as .*COCO* files (a standardized format for image annotation) to input them into the models. We used artus (10.5281/zenodo.8014190) (Talpaert Daudon et al., 2023), an open-source Python package, to fine-tune a deep learning model coming from the *Detectron2* package (Wu et al., 2019) and spatialize model predictions. The pre-trained model chosen is an X101 pre-trained on ImageNet. This model was chosen from the Detectron2 models' benchmark (Wu et al., 2019b) because it had the best performance on the ImageNet dataset. The pre-trained model tested two different numbers of iterations on the same trained images: 10,000 and 20,000 iterations (Table 6). Before training, we partitioned the 832 annotated images into 80 percent for training (665 images), 10 percent for validation (84 images), and 10 percent for testing (83 images). We retained the distribution of classes across the subsets. We trained the models with 2 images per batch, a learning rate of 0.00025, 1 GPU (Quadro RTX 4000), 32-core CPUs, and 64 GB of RAM.

For selecting the best-performing model, we used the average precision for 50 percent of intersection over union (AP50), meaning predictions of boats were only counted as correct when they overlapped 50 percent of the ground-truthed bounding box annotations and corresponding to the right type of vessel. As a CSV file, we exported class attributes for these predictions to calculate performance by the yes/no/maybe categories.

We then evaluated the trained model on the test dataset and exported summary statistics, summarizing total and average vessels by annotation class and false positive/true positive. It is

[6] Note: Results on LOA for "yes" (i.e. gillnet) are preliminary, and this portion of the analysis is ongoing.

important to note that the annotations are only for 10 percent of total images (i.e., test dataset), so they cannot be used to estimate total boat counts like the manual annotations in this application.

Researchers visualized all models and corresponding predictions in FiftyOne Teams, a cloud-based data visualization system that allows analysts to work remotely and simultaneously (Moore and Corso, 2020) (Figure 5).

Figure 5. Screenshot of the FiftyOne Teams platform

B. WorldView-3 imagery analysis

In addition to the Google Earth Pro imagery, we trialed using VHR imagery as *.tifs* to detect vessels. Due to a limited budget, we were unable to purchase VHR images and instead acquired two 4-band WorldView-3 images courtesy of the European Space Agency (ESA) of the port of Karachi (Source: Worldview-3 image by © MAXAR (2023) - obtained within ESA's TPM programme). Our quota for the images allowed for tasking and retrieving one archival image, both collected over the Karachi fish harbor (Table 6). We collected both in the spring months, anticipating higher density of vessels in port at this time of year. For the tasked images, other tasking requests to the European Space Agency and cloud coverage limited the two-week range we requested from the European Space Agency.

We used *artus* to run the best-performing model from the Google Earth Pro analysis, “ITER20000_X101,” on these two images. We exported predictions as *.geojsons* into QGIS, clipped the annotations to the spatial bounds of the Karachi harbor polygons, and then selected only annotations with a confidence interval of over 50. We then calculated summary statistics on these two images as done with the GoogleEarth Pro images to summarize the number of boats. Using QGIS, we are in the process of measuring these boats and conducting the analysis on both WorldView-3 images.

Table 6. Description of WorldView-3 images

Image Name	Image date	Harbor	Processed band order	Cloud coverage	Processing	Image off Nadir	Ground Sampling Distance (GSD)
050150757020_01	May 30, 2023 (tasked)	Karachi	RGB	0-1%	4-band pansharpened		30cm
015784715010_01	April 2022 (archived)	Karachi	RGB	0.0%	4-band pansharpened	15.5	33cm

C. Surveys

We conducted a pilot survey with captains and crew of gillnet fisheries (inclusive of all gillnet fisheries, not tuna), led by WWF Pakistan to better document cetacean bycatch in the fishery. We have conducted 27 surveys thus far in the Karachi fishing harbor and Ibrahim Hyderi, a nearby small fishing village, focusing on bycatch in gillnet fisheries (Figure 6). WWF Pakistan opportunistically approached captains and crew, obtained oral consent, and shared an 18-question survey with the respondents in Urdu (Appendix I, Duke IRB protocol: 2022-0507). The surveys are ongoing, and we aim to contain 90 tuna gillnet surveys total in Karachi and Gwadar. All surveys have so far taken under 10 minutes each.

We will use summary statistics and generalized linear mixed-effects models (GLMMs) to analyze results. Predictor variables are fishing method (surface or subsurface drift gillnet setting), net length, horsepower, and vessel length, whereas captain/crew is a random effect; response variables are total bycatch, bycatch fate (e.g. released alive or mortality), and month. Next, we will select the best model based on Akaike's Information Criterion (AIC; Akaike, 1998) (Kiszka et al., 2021). Models with the highest AIC weight will be selected. Then we will will calculate conditional and marginal Nakagawa's R2 to explore the amount of variance (Nakagawa & Schielzeth, 2013). Researchers are analyzing data in RStudio version 4.3.1.

Figure 6. Surveys conducted with captain and crew in the Karachi fishing harbor.

IV. Results

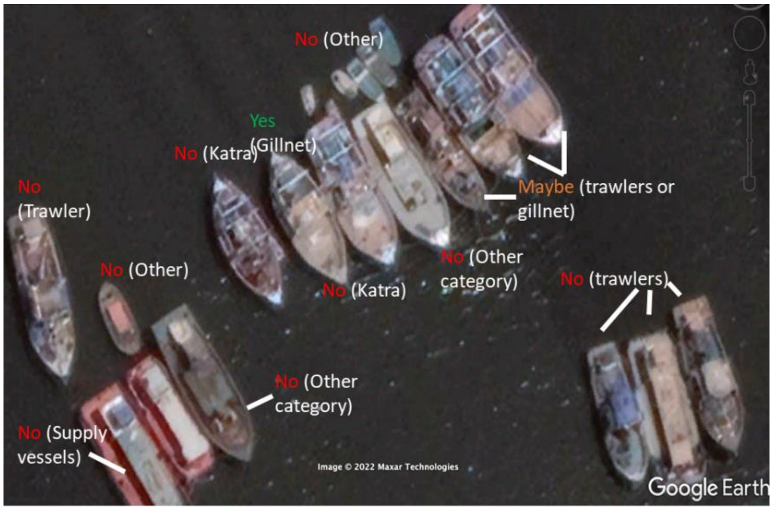
We briefly summarize results of each sub-component of the analysis, but we urge caution in interpreting the results as providing definitive estimates of the fleet size given uncertainties and the preliminary nature of the methods described in this paper.

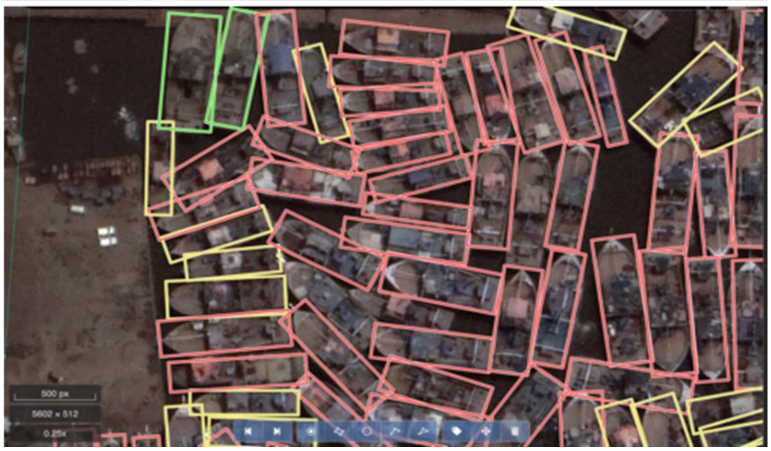
A. Google Earth Pro manual image annotation analysis

a. Boat counts via Google Earth Pro image annotation

We manually counted a total of 20,052 boats in this analysis for the two-year period in BIIGLE, inclusive of all vessel types within the AOI. In total, we annotated the most vessels in Karachi overall (n=14,868), followed by Gwadar (n=4,862), and Pishukan (n=305). Nearly two-thirds of vessels occurred in the “no” category (n=14,029), followed by vessels labeled as "maybe" (n=3,499), and then vessels labeled as “yes” (n=2,507) in both years. Most “no” vessels were small, likely non-motorized boats; the “maybe” category typically included vessels in Karachi that were ambiguous between a trawl and a gillnet vessel (Figure 7).

Figure 7. Top image: Example of several different vessel types in Karachi. Bottom image: Example of annotated image in Karachi using BIIGLE. Green boxes represent gillnet vessels “yes” category; yellow boxes represent vessels analyst unsure about (“maybe”); red boxes are not gillnet vessels, likely trawls and other vessels.





For the seasonal total (April and May 2021 and 2022), which we find to be a better representation of fleet size than aggregate counts to avoid double counting and capturing ports at a time of highest port density, we calculated 601 tuna gillnet vessels (SD +/- 41.87) (Table 7, Figure 8). We counted the highest number of “yes” vessels overall in Karachi (360 +/- 13.86) during this season, followed by Gwadar (230 +/- 12.79), and Pishukan (11.00 +/- 0.00). Karachi also had 97 percent of the “maybe” annotations for all three ports during this season. Overall, we counted 4059 (+/-195.41) vessels across all three annotation classes for this period, roughly one-fifth of total boats.

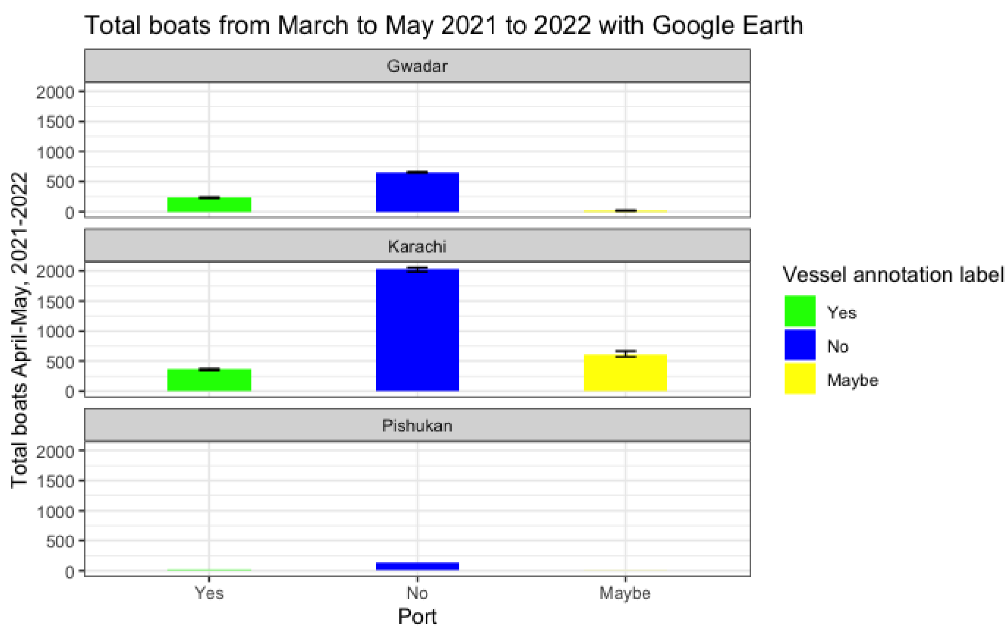
Table 7. Total boats from April-May 2021 and 2022

Category	Gwadar	Karachi	Pishukan[7]	Total
Yes	230 (+/- 12.79)	360 (+/- 13.86)	11	601 (+/- 41.87)

[7] Because imagery was not available for Pishukan at 700-750 ft eye altitude, these data represent boat counts for March 2022.

Maybe	16 (+/- 3.83)	620 (+/- 49.12)	2	639 (+/- 108.26)
No	656 (+/- 9.56)	2019 (+/- 34.40)	132	2807 (+/- 267.67)
Total boats	905 (+/- 69.22)	3008 (+/- 264.85)	146	4059 (+/- 195.41)

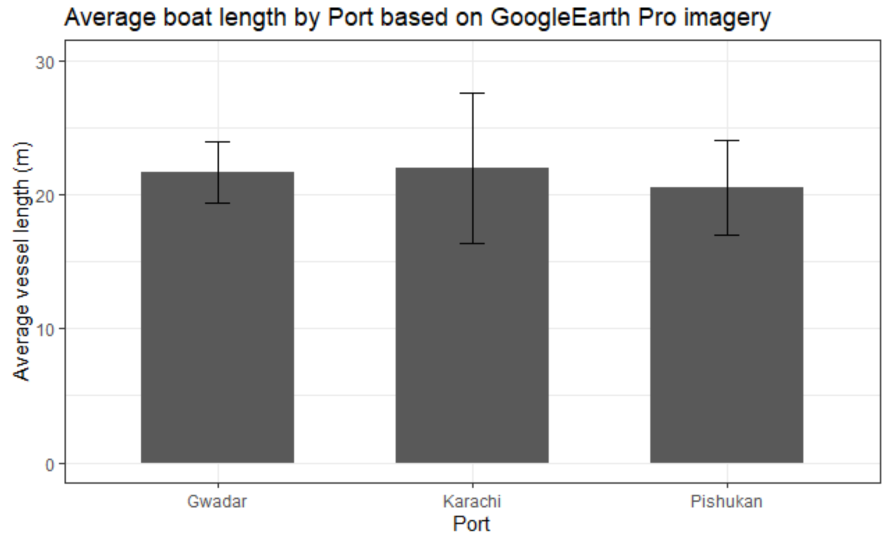
Figure 8. Total boats by port and category from April-May 2021 and 2022 for Karachi and Gwadar, and March 2022 for Pishukan



b. *Average vessel length overall (m)*

Vessel size ranged from 15.38 meters to 26.89 meters LOA across sampled vessels (*n* = 75). Vessels in Karachi had the highest average LOAs, followed by those in Gwadar and Pishukan; vessels in Pishukan, however, had the most significant variability in size and included the highest maximum vessel length (26.89 m; Figure 9). All ports hosted vessels over 24 m LOA, which could be considered industrial by some criteria.

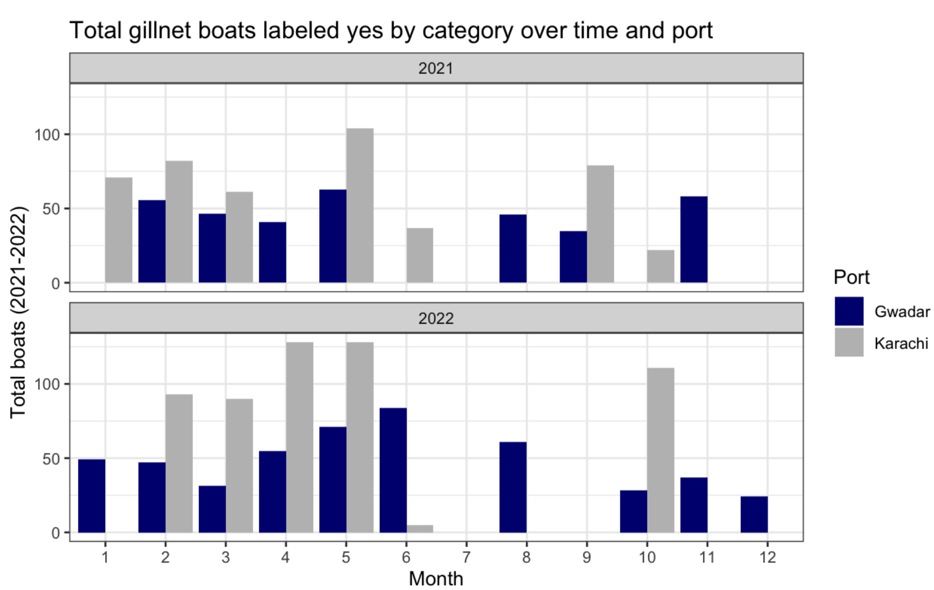
Figure 9. Average LOA of vessels from Google Earth Pro images, randomly sampled (n = 75) from all vessel annotations and summarized by port.



c. Temporal trends

Determining seasonal patterns in gillnet vessel presence was challenging due to lack of consistent image availability in the Google Earth Pro dataset. However, of months with available imagery, the top three months with the highest number of "yes" vessels were July 2018 (Pishukan), April 2022 (Karachi), and May 2022 (Karachi) (Figure 10). We note that we counted more "yes" vessels overall in 2021 (1,319) than in 2022 (1,188) (even though more images were available in 2022), but we do not find this yearly difference significant.

Figure 10. Total boats over time for Gwadar and Karachi (note: count data, not seasonal average data)



B. Deep learning from Google Earth Pro training data

a. Model Performance

Both models had strong overall performance in detecting gillnet vessels with little difference observed between 20,000 vs. 10,000 iterations (AP50 >60 for each) (Table 8). The models performed best at detecting vessels in the "no" category, with the "maybe" category having the lowest AP. The model with fewer iterations performed better at detecting the yes category.

Table 8. Overview of machine learning models for Google Earth analysis

Model Name	AP(50)	AP-Maybe	AP-No	AP-Yes	Model parameters
ITER20000_X101	63.49	13.1	63.6	35.6	20,000 iterations of non-augmented samples; pre-trained on ImageNet dataset
ITER10000_X101	64.1	13.5	63.9	37.2	10,000 iterations of non-augmented samples; pre-trained on ImageNet dataset

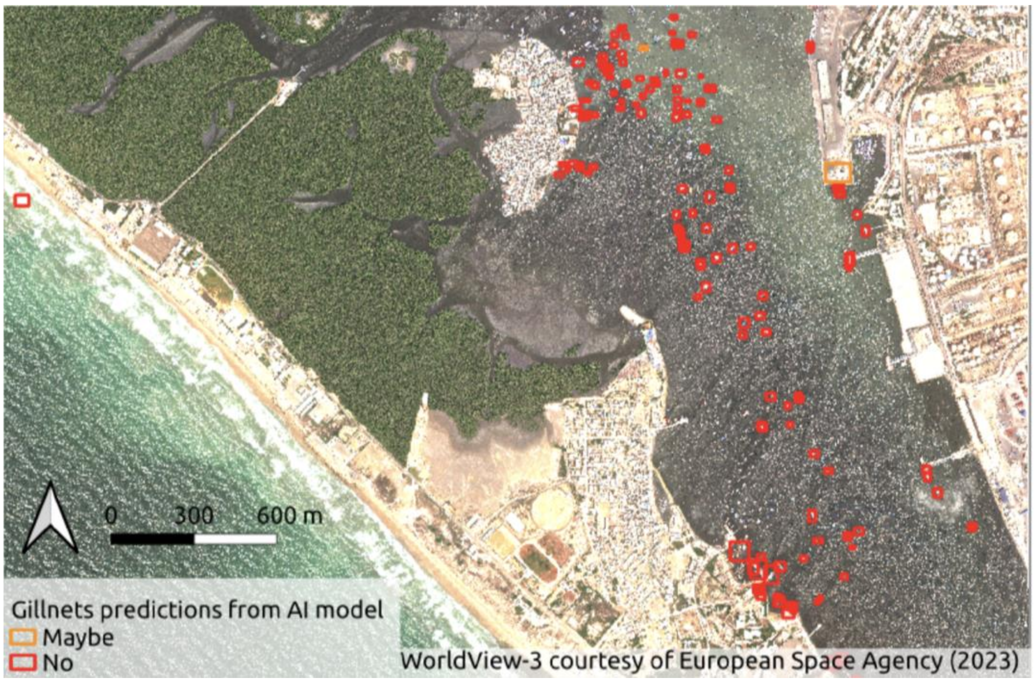
b. Results

In a test set of 83 images, the best performing model (ITER20000_X101) detected 4,182 (unvalidated) vessels in total. Nearly half of the vessels were in the "no" category (n=2,504), followed by the "maybe" category (1,209), and the "yes" category (n=469) (based on unvalidated counts and classifications). Karachi had two-thirds of the vessels (n=2,897), followed by Gwadar (n=1,177), and Pishukan (108). The analysis is ongoing.

C. WorldView-3 model performance and results

We are still analyzing results from the WorldView-3 analysis; so far, we have tested both models on one image of Karachi (Figure 11). The models have not detected any "yes" vessels, which may result from an incompatibility between the model, being trained on 3-band Google Earth Pro imagery, and the 4-band worldview imagery of the test dataset. We will continue to attempt to estimate boat length and number of boats by annotation class in these images. Notably, images received from ESA are large (area of 25 km2) and extend beyond our specific AOIs in Karachi; we are clipping that AOI to our polygons in Karachi.

Figure 11. Model predictions on a World-View 3 image in April 2022 of Karachi (note: this specific image is outside our AOI within the Port of Karachi - we are in the process of clipping this large image to our specific AOI)



V. Discussion

The use of satellite image technology and corresponding deep learning models is rapidly expanding in ecology and fisheries. Our study set out to determine if tuna drift gillnet boats can be described, counted, and measured using VHR imagery. Here, we describe three methods to describe the Pakistani gillnet fleet based on stationary boats in port: 1) manual image annotation, 2) development of deep learning models on satellite imagery, and 3) port surveys. Early, working results show that VHR imagery (e.g. < 50 cm GSD) at high resolution can detect gillnet vessels under 24m LOA and even small vessels. However, nuances of the fleet, local context, and ground truthing impact the utility and relevance of analyses based on this imagery. We discuss each methodology, challenges, and lessons learned, and make recommendations for future applications of this work based on lessons learned in this project.

A. Information about the gillnet fleet

Manual counting most comprehensively characterized the current fleet composition among the methodologies that we examined, largely because the deep learning models only run on a subset of training (83 images) and testing data and the WorldView-3 testing dataset consisted of only two images of Karachi. These findings suggest that the Pakistani tuna drift gillnet fleet includes at least 601 (SD +/- 41.87) tuna drift gillnet vessels in the fleet, but almost certainly more when accounting for vessels at sea and in other harbors not included here. Karachi has the highest number of vessels, followed by Gwadar and Pishukan. According to the Google Earth Pro imagery, the months of July, April, and May yielded the most annotated gillnet vessels in port. This mirrors previous information reported by WWF Pakistan (Khan 2018; IOTC 2019b).

While we share this fleet size estimate here, we strongly urge caution in interpreting this as an accurate representation of the size of the Pakistani drift gillnet fleet. Firstly, this estimate is based on the manual analysis, and human error (e.g. incorrect annotation, attention fatigue, increasing familiarity with the dataset, etc.) likely introduced biases into the total vessel count (particularly in the “maybe” and “yes” categories). As discussed below, it was often difficult to distinguish between trawl and gillnet vessels in Karachi, and given the number of vessels in Karachi, standard deviation is a conservative estimate of variance in this count estimate in this estimate. Secondly, this estimate is limited in space and time. Spatially, it only accounts for vessels in three ports and also excludes vessels that may be actively fishing at sea. It also averages vessels using imagery from only two months within each year over only two years. A longer-term dataset would better describe trends over time at a scale that more closely matches the observed decline in catches in recent years (Khan 2021a). Finally, the fleet size estimate does not include vessels in the “maybe” category, which some are likely includes some gillnet vessels. This estimate should be inferred cautiously, but likely represents a conservative underestimate, given these factors.

Beyond a coarse estimate of the number of gillnet vessels, this research demonstrated that most vessels fall under 24 m LOA, with an average LOA of around 21 meters. There were instances, in all three ports, of vessels slightly exceeding 24 m LOA. Per IOTC Resolution 19/04, any vessel over 24 m LOA should be on the IOTC Record of Authorized Vessels. At the time of writing, Pakistan has no current vessels listed on the IOTC Record of Authorized Vessels. However, they previously had ten vessels listed between 2011 to 2013, all of which were gillnetters (IOTC 2023).

Beyond the work published by Khan (e.g., 2011, 2018, 2021, etc.), Nawaz and Moazzam (2014), and Kiszka et al. (2021), there remains little information about the fleet. Nevertheless, the findings here corroborate the limited, existing information. Other figures point to 700 gillnet vessels in the Pakistani fleet, based mainly in Karachi and Gwadar (Khan 2021b). While we examined vessels in Karachi, Gwadar, and Pishukan harbors in this study, tuna vessels are also based in Ormara and Jiwani (IOTC 2020).

At the time of writing, it appears that Pakistan does not publicly release registered vessels or fishing authorizations (Global Fishing Watch and Trygg Mat Tracking, 2020). AIS use is limited, but VHR imagery has identified some Pakistani and Iranian vessels on the high seas and Somalia and Yemen’s EEZs. However, fishing patterns are not well understood due to the lack of AIS and VMS (Global Fishing Watch and Trygg Mat Tracking, 2020). There is also evidence of Iranian vessels operating in Pakistan fishing harbors (Global Fishing Watch and Trygg Mat

Tracking, 2020) and/or sharing flags, particularly in the western harbors in Pakistan (WWF personal communication, 2023).

Beyond these statistics, this study has documented the key features of the design of a Pakistani gillnet vessel. It shows how it can be differentiated from other vessels via satellite imagery. In this fishery, a gillnet vessel has a flat stern, space between the bow and deck house, and should not have visible cranes (Figure 12, Table 4). Other features define these vessels but were challenging to identify with satellite imagery, such as boats operating from Karachi are said to have a transom at the stern. In contrast, boats in Gwadar are double-keeled (IOTC 2020). Trawl vessels share many of these same features but are often distinguishable by visible cranes and blue-colored awnings (Figure 12b). Katra, or seine vessels, are more easily distinguished as being "double-edged," having a pointed bow and stern (Figure 12c).

Recommendation 1: *For future work to better understand the Pakistani gillnet fleet, we recommend: 1) extending the AOI to the EEZ, particularly high-density fishing areas like the Indus Delta; 2) expanding the spatial coverage of this study to all ports; 3) ensure ground-truthing can be conducted for Karachi to better distinguish between trawls and gillnet vessels. For other national fleets, it is critical to ensure a baseline understanding of similarities and distinguishing differences between vessel types at the study's outset.*

Figure 12. Examples of a. gillnet vessels (Gwadar), b. trawl vessels (Karachi), and c. katra vessels (Karachi) in June 2022 taken as screenshots from Google Earth Pro. Here, the gillnet vessels are distinguished by the flat stern and pointed bow, but differentiated by the trawl vessels that have a pink awning (left boat) and visible crane (right boat). The katra vessels have a pointed bow and stern.

B. Lessons learned about fishing vessels in computer vision and object detection

Here, we explain some of the trade-offs and lessons learned through trialing different methodologies for satellite imagery analysis.

a. Image annotation software comparison

Preprocessing of remote sensing data for image annotation, whether for manual counting or deep learning applications, requires steps of raw data acquisition and storage, then tiling, subsetting and storage in an organized and programmatically accessible scheme. The next step is typically manual-visual image annotation of OOIs across the entire dataset by human analysts, whether for manual counting or for the training and testing of deep learning algorithms. In our study, we used three annotation classes ("yes," "no," and "maybe"), but the number of classes can vary based on the study design and purposes. Images can be annotated in a variety of ways, depending on their data types, anticipated workflow and target results. For this study, we manually annotated OOIs using bounding boxes, rather than masks or irregular polygons, and we used object detection methods rather than image segmentation—these alternatives represent other common practices in image annotation and computer vision.

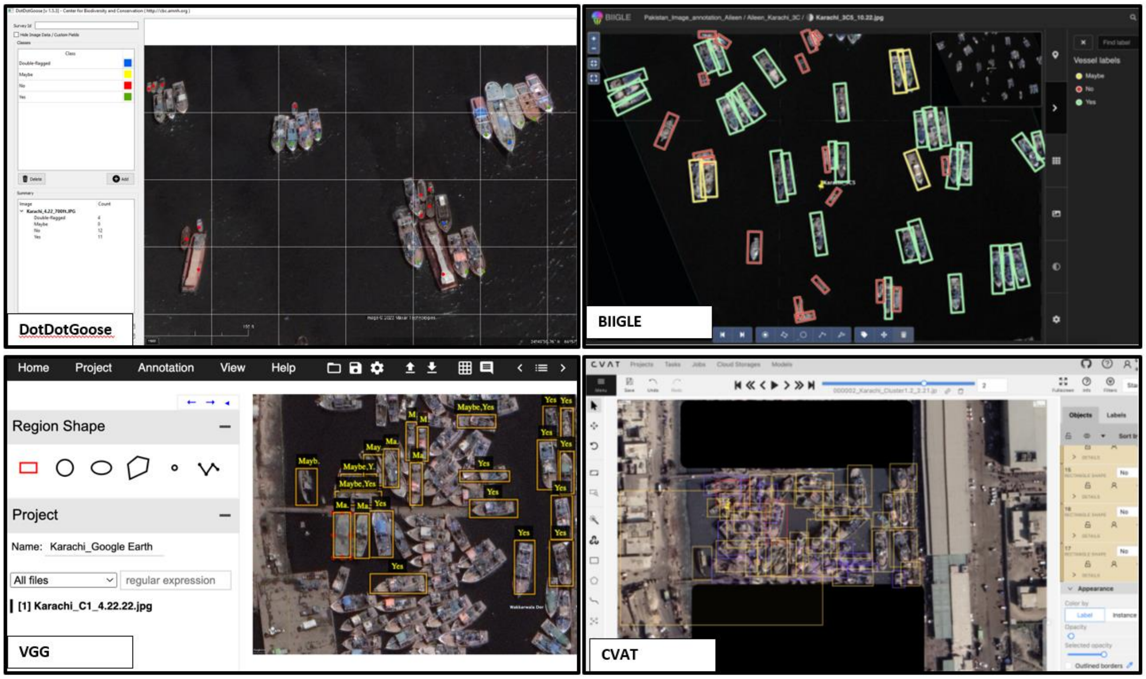
Object detection describes a process of analysts or algorithms identifying and annotating instances of an OOI across imagery—in this case, vessels, to better understand the number of boats. Segmentation describes a process of partitioning imagery into contiguous segments of irregular polygons, based on visual, spatial and/or spectral characteristics, to which analysts or algorithms assign classes. For example, a study seeking to describe biodiversity in a coastal habitat might segment all parts of an image, considering that all segments belong to classes that are of interest to the study. In contrast, for our study, we just annotated our specific OOI, considering that other features and spaces were not germane to our study (Weinstein 2018, Khan et al., 2023). We annotated OOIs with bounding boxes, among alternative shapes, for several reasons: 1) Given the density of vessels in ports, choosing a rectangle over a circle reduced the overlap between annotations – which was important for deep learning models. 2) Boxes were also critical for training models later on, rather than simply placing a dot on a boat, as we needed pixels, shape, and other features of the boat to be detected by deep learning models. In retrospect, segmenting the entire image and hand-drawing a feature (a "mask") would have been more effective for deep learning, given the dense cluster of vessels in some areas and the similarities between some vessels. While rectangles would be effective for vessels at sea, the density of vessels in ports caused considerable overlap in the bounding boxes, which may have confused the deep learning models. Model AP based on bounding boxes versus masks for fisheries would be an interesting methodological case study in the future.

As noted in the methods, we first tested five different applications for manually annotating Google Earth Pro imagery (Table 9, Figure 13). The number of image annotation options are rapidly increasing, and applicability varies by study design. While we found BIIGLE effective for our purposes, annotating areas with a high density of vessels, CVAT also offered the same capabilities for rotating bounding boxes and offered linkages to custom deep learning models. Therefore, CVAT may be a valuable option for studies using deep learning in the future, though CVAT does seem to require users to pay, unlike the other software we used. We recommend reviewing Weinstein (2015) and Khan et al. (2023) for further description of key terms for computer vision with applications to ecology and an overview of other image annotation platforms.

Table 9. Comparison of applications for manually annotating OOIs in a satellite image.

Program	Trade-offs of program	Online platform (O) or downloadable software (S)	Measure boats	Free of charge?
DotDotGoose	Pros: ● Georeferencing capability for points ● Allows user to tile image in platform Cons: ● Dots not conducive for machine learning ● Cannot measure in platform ● Very specific file saving structure	S	No	Yes
VGG Image Annotator	Pros ● Multiple annotation layers Cons ● Cannot measure or rotate boxes	O	No	Yes
BIIGLE	Pros: ● Can rotate labels on an image – good for clustered boats Cons: ● Cannot measure boxes without georeference	O	No	Yes
QGIS	Pros: ● Easily measure vessels Cons: ● Less automated than other platforms	S	Yes	Yes
CVAT	Pros: ● Can link to deep learning models ● Can rotate image annotations Cons: ● Not georeferenced	O	Yes	No

Figure 13. Screenshot of image annotation editors for DotDotGoose, BIIGLE, VGG, and CVAT



Recommendation for future work: *For future studies, careful consideration should be given at the design stage of the study to decide on annotation programs: 1) the degree of overlap between objects of interest and if segmentation or detection is needed to inform program selection; 2) determine if manual annotations will be fed in deep learning models to inform program selection; and 3) determine if the purpose is counting, description (e.g. measuring boats, georeferencing OOIs), or segmentation. Additionally, careful attention needs to be given to consistent file naming conventions to reduce data clean-up.*

b. Deep learning models and trade-offs

Researchers developed several deep-learning models here using the *artus* (Talpaert 2023) open-source Python package, and then highlighted them in FiftyOne Teams for ease of team-based analysis. The models used here varied in the number of iterations.

Overall, we found that deep learning detections for this study are valuable, but confidence levels varied by class and port. Data-augmentation techniques were tested during training but resulted in worse accuracy than without data-augmentation techniques. Using a small sample size of predictions produced by the models and then ground-truthed by the analyst in CVAT helped improve model performance. However, there was still variability given the confusion between the yes and maybe categories.

In this study, many factors influenced model performance. We assume that the variability in the "maybe" category of vessels in Karachi increased variability in the models and led to poorer model performance, given the challenges for a human analyst to distinguish between trawl and gillnet vessels in Karachi. There was much less variation in Pishukan and Gwadar, given the background knowledge provided by WWF Pakistan that the vessels in these two ports were likely almost exclusively gillnet vessels if they met the basic criteria of the vessel design. The models would have likely been improved if they were explicitly run for each study site. However, there is a careful balance here of a reduction in training images if the models were separated by port area. We also determined that running the models by port was likely not germane to the objectives of this study.

While Python was used to build and train models, computer vision and machine learning is a rapidly growing field with additional options being put forward for stakeholders needing to employ machine learning. While other well-established tools could have been used to train a CNN (e.g., ResNet variant implemented in Keras Tensorflow 2.0 or Pytorch), options exist for human-in-the-loop deep learning for those with more limited knowledge of computer vision. For example, the recent open-source Annotation Interface for Data-driven Ecology (AIDE) platform may also be used to accelerate vessel detections (Kellenberger et al., 2020). AIDE is a web-based, open-source platform that integrates active machine learning and annotated labeling, which is a promising new and efficient feature that frees analysts from manual labeling (Kellenberger et al., 2020).

Recommendation for future work: *For future studies employing deep learning on fishing vessels, we recommend: 1) Ensuring there are enough training images and annotations to train a model effectively, 2) Determining if deep or machine learning is necessary, and considering the trade-offs between manual analysis for a small spatial area/small sample v. a larger area juxtaposed to human resources and time to train a model, 3) Account for local specifications to the study site that may impact the model.*

C. Comparing satellite image sources

This study leveraged optical satellite imagery from two sources: Google Earth Pro (mosaiced from different sources) and WorldView-3, courtesy of the European Space Agency. At the study's outset, we aimed to acquire additional VHR satellite imagery, particularly from Planet's SkySat (50cm resolution), for 1) additional spatiotemporal coverage of vessels and 2) to compare satellite image sources. At the time of writing, we are unable to purchase images due to the high cost of these VHR images, particularly for tasked images. We could only acquire the two WorldView-3 images that we did because of the European Space Agency's Third Party Mission, which we could obtain free of charge due to colleagues based in Europe on this project. Without this access, we are unaware of other pathways to acquire sub-50cm VHR imagery at a low cost without turning to Google Earth Pro.

There are, however, trade-offs between the two sources. While Google Earth Pro is free, easy to access and download, and easy to navigate, a notable drawback is that the images themselves are not georeferenced at download as they are only downloadable only as *.jpgs* or *.png* files. That being said, polygons and other features from Google Earth Pro are available as downloadable *.kmz* or *.kml* files that can then be loaded into geographic software, or images can later be georeferenced in software such as QGIS (for example, see: https://github.com/jsoma/clipped-and-georeferenced-images-from-google-earth-in-qgis-3), but these approaches add extra time and inefficiencies into the analysis. We found that the lack of georeferenced images at download also impeded our workflow to measure vessels, which is critical for applications to IOTC management of this study. We, therefore, had the option to measure vessels in Google Earth Pro with the ruler tool and cross-check vessels with annotated vessels in BIIGLE – also an inefficient method – or try to estimate vessel length based on the number of pixels and bounding box length from BIIGLE. Further, Google Earth Pro users are limited to existing imagery across spatiotemporal scales; thus, coverage is often limited and unavailable in real-time.

On the other hand, VHR imagery like World-View 3 offers incredibly high-resolution images that are georeferenced (*.tiff or .tff* files), available in different bands depending on the scope of the analysis. VHR imagery can also be tasked within a two-week window to pinpoint specific time-area study sites. However, the costs are extremely high, and the storage for these images will likely require some type of external or cloud-based drive due to image size.

Thus, while the literature can refer to VHR imagery as more robust and able to feed into more complex analyses, we found here that Google Earth Pro is a potential low-cost tool with relatively high spatiotemporal coverage that should not be overlooked. Both Google Earth Pro and VHR sensors offer strengths and should be considered alongside project objectives (e.g. just counting vessels over a historical time series or real-time detections) and costs.

D. Challenges

While this study has demonstrated that object detection via different satellite sources is possible for semi-industrial or smaller vessels, we encountered several challenges specific to the nature of our study site and design. We share these here as lessons learned for future research on vessel-detection studies.

Assumptions: First, we assumed that any vessel counted as “yes” is an active vessel and therefore counted as part of the current fleet; at present, these vessel counts are not linked to AIS, VMS, or catch statistics that would verify whether a vessel in port is actively fishing. Second, it does not account for vessels at sea fishing during this time and thus does not provide a comprehensive estimate of the entire fleet. It also does not account for vessels double registering between Pakistan and Iran, including those that may be in Iranian ports at the time of screen capture. Finally, we likely double-counted a subset of some vessels, both manually and in machine-learning models, given recurrence in images and because of the density and overlap of vessels between images.

Gillnet and trawl vessels: We could not successfully task a satellite image while conducting real-time ground truthing verification in port, which would have helped verify uncertainty in the “maybe” category. It was often challenging to decipher a tuna drift gillnet from a trawl vessel over satellite imagery in Karachi, where many gillnet and trawl vessels look similar from a bird’s eye view. These vessels have several features that look quite similar: similar vessel shape and length and poles/cranes at the bow of the vessel. Indeed, these vessels may even engage in gear-switching, increasing the challenges of deciphering some similarities. From an eye-level view (Figure 14), it is easier to tease them apart; from a bird-level view, deciphering the type of vessel was often challenging. In those instances, the analyst took a conservative approach and assigned the vessel as a "maybe." While this was a challenge in Karachi, identifying tuna drift net vessels is relatively easier in Gwadar and Piskuhan. Furthermore, we used a rather simple suite of three annotation classes. Had we created more annotation classes, such as "maybe – gillnet or trawl" or "maybe – other purpose," we would have been able to conduct additional sensitivity analyses that would have provided further context for the "yes" class of gillnet vessels.

The nature of this study (i.e., being limited to ports) did not allow for extrapolations to bycatch estimates based directly on satellite imagery. This is a critical constraint given the increasing bycatch of cetaceans and other protected species in the Indian Ocean gillnet fisheries. In the future, real-time tasking via Planet SkySat or WorldView-3, combined with objection detection and machine learning, may be a promising technique to detect both vessels and whales to better understand interactions.

Figure 14. Eye-level view of gillnetters and trawlers

General: Challenges associated with this type of work include resource availability (e.g., costs to purchase images, storage, human power to manually count vessels to train a model); limitations due to spatiotemporal coverage (e.g., due to cost, cloud coverage, archived or tasked images); local context (e.g., if there are vessels that gear switch and resemble each other; image availability in highly industrial or militarized areas, etc.); and finite details of the methodology (e.g. overlap in bounding boxes, avoiding double-counting of vessels between vessels overlapping in images, selecting annotation classes). However, with careful consideration of methods at the outset of the study, these can be easily addressed in an efficient workflow, particularly as computer vision applications and tools become more accessible (Figure 15).

Figure 15. Overview of key challenges and lessons learned from this study

Challenges

- Trade-offs between Google Earth Pro and VHR imagery
- Consistent imagery availability across spatiotemporal scales
- Deciphering tuna gillnet vessels v. trawl vessels from space
- Extrapolating to an entire fleet size
- Cost of VHR satellite imagery

Lessons Learned

- In general, semi-industrial gillnets can be detected (i.e. counted) via high resolution imagery
- GoogleEarth offers free, open-source imagery
- Real-time imagery best for ground-truthing
- Suggests this may be a powerful tool for improving effort and bycatch estimates, but data imprecise
- Careful attention needs to be provided at the outset into image annotation planning (e.g. annotation classes, shape, storage, and other)

E. Implications for management at the IOTC

This work sheds light on Pakistan's tuna drift gillnet fleet, for which accurate reporting and statistics at both the national and IOTC level is limited. This study demonstrated that most vessels in the fleet occur within the proposed "semi-industrial" range between 15-24m LOA. These findings point to two crucial implications. First, given that there were several instances of vessels over 24m LOA, these vessels would be considered "industrial" per IOTC Resolution 19/04. Karachi had the highest frequency of vessels over 24m LOA and the highest sampling and spatial coverage. However, it is essential to note that we do not have evidence of the vessels fishing at sea or any information on their catch, and for vessels fishing outside the EEZ but under 24m LOA they would also be subject to requirements under IOTC Resolution 19/04. Secondly, given that most vessels are *under* 24m LOA, this indicates that the lack of IOTC reporting requirements for vessels of this size severely hampers the ability of the RFMO to monitor and manage the tuna fisheries under their jurisdiction.

F. *Future Research*

Specific to Pakistan, we recommend expanding the scope of this analysis to other ports in Pakistan and the EEZ to provide a full picture of the size of the fleet. Furthermore, given the sharp decline in Pakistani catch in recent years, it would also be helpful to extend the time series of this study and monitor the number of boats before the 2018 decline in tuna catch.

While this analysis can help provide baseline information on the size and general characteristics of the fleet, it is arguably an inefficient approach. Instead, using AIS coupled with a vessel registry would be most efficient – ideally if supported by incentives, which have been shown to be effective in other fisheries and bycatch scenarios (e.g., Lent and Squires, 2017;

Squires et al., 2021). To work towards this, we suggest pilot studies on incentives for better monitoring. Specifically, we recommend studies exploring: 1) Incentivizing captains to have their vessel name and length/gear type on an informal vessel registration list, either with a form of payment or other incentives. This list could be held by the Pakistani government and/or IOTC; 2) we also recommend funders and managers consider an incentives-based program to help push forward the use of AIS on tuna gillnet vessels from all ports, which will greatly enhance understanding of vessel fishing patterns – and reduce any duplications in in-situ port counts.

In addition to the same incentivized monitoring projects, we recommend repeating this analysis's Google Earth Pro portion for other IOTC flag states to better understand fleet size and trends over time. The Google Earth Pro portion of the analysis is a low-cost and manageable analysis for stakeholders that may be a suitable first step. In particular, we recommend conducting a similar analysis for other major gillnet fleets concentrated around the Arabian Sea: Iran, India, Oman, and Sri Lanka.

Acknowledgements:

The authors gratefully acknowledge the World Wide Fund and the National Geographic Society for generous grants to conduct this work. We also thank the French Embassy in the U.S. and the Chateaubriand Fellowship Program for supporting BE to conduct research with IFREMER and IRD. Finally, we thank the European Space Agency for providing two World-View3 images (Worldview-3 image by © MAXAR (2023) - obtained within ESA's TPM programme).

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Appendix A:

Revised served about Pakistani tuna gillnet fisheries and bycatch

August 2023

Date:_____________________ **Port:______________________________**

Form #:___________________ **Consent Received (Y/N):______________**

Background questions:

1. Do you fish primarily in the tuna gillnet fishery? (Please circle one)

   Yes ________________ *No ________________

**Note: If no: please conclude the survey. We only want to interview owners, captains, and crew that fish for tuna with gillnets.*

2. If yes, what is your role in the tuna gillnet fishery? (Please circle one)

   Owner **Skipper/captain** **Crewman/sailor**

3. What is the horsepower of your gillnet vessel? ________________
4. What is your gillnet vessel length? ________________

Fishing and catch questions:

5. How many gillnet fishing trips do you make per year? __________________
6. How long does each gillnet fishing trip last? ___________________________
7. How many gillnet sets do you deploy per trip? _________________________
8. On average, how many hours is the gillnet soak time for each tuna set? ________
9. What is your estimated gillnet net length? (km) _______________
10. What is the stretched mesh size of the gillnet? (cm) ____________________
11. What material is the net made from? (Please circle one):

Multifilament **Monofilament** **Other (please list):___________________**

12. What is your estimated catch per trip? (tons) ____________________
13. What type of tuna gillnet are you fishing? (Please circle one):

Surface **Subsurface** **Both**

14. During which months of the year do you fish gillnets for tuna? Please circle:

January	**April**	**July**	**October**
February	**May**	**August**	**November**
March	**June**	**September**	**December**

15. What do you do in the closed season fishing season? ___________________________

16. If you are comfortable to share,

    How much is your share per trip? ___________________________

    How much is your total earnings in a year? ___________________________

17. If you are comfortable to share, what are your:

    Net setting coordinates ____

    Net hauling coordinates ____

18. What are the target species that you catch with tuna gillnets?

____

____

Bycatch questions:

19. Do you ever experience any bycatch of marine mammals or sea turtles in your tuna gillnet? (Please circle one)

Yes **No** **Unsure**

If no or unsure, please skip 16a, 16b, and 16c. If yes:

19a. Which marine mammal or turtle species are entangled in your tuna gillnets?

____

____

19b. Which months do you experience bycatch mostly in the tuna gillnet fishery? Please circle:

January	**April**	**July**	**October**
February	**May**	**August**	**November**
March	**June**	**September**	**December**

19c. Approximately how many animals were caught accidently in a year?

Marine mammals:__________________

Sea turtles: _________________________

Others (Please specify): _________________________

20. What do you do with the bycatch after an animal is captured in the tuna gillnet fishery? Please circle:

Retain **Discard** **Release alive** **Release dead** **Transship it**

21. Is there anything else you wish to share with regards to bycatch or tuna gillnet fishing?