Update on characterizing the Pakistani tuna gillnet fleet through satellite imagery: preliminary summary of results and next steps

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Abstract
Information on bycatch is limited in many global fisheries, including in Indian Ocean tuna drift gillnet fisheries. The existing data that does exist for the Indian Ocean suggests that bycatch rates in tuna drift gillnets may be very high, particularly for cetaceans, though the data is scattered and incomplete. Most drift gillnet fleets in the Indian Ocean are comprised of relatively small vessels that are poorly documented. This is in contrast with purse seine and pelagic longline fleets operating in this region, for which fleet classification, fishing effort, and target catches are better documented and subject to more reporting requirements under the Indian Ocean Tuna Commission (IOTC), the regional body for managing tuna fisheries. Considering existing data gaps, this study leverages satellite imagery and machine learning to better understand tuna drift gillnet fleets in the Indian Ocean, with Pakistan as a case study. This study aims to quantify and describe the Pakistani tuna drift gillnet fleet using satellite imagery to quantify and describe tuna drift gillnet vessels in port. A total of 5648.25 boats were counted in this study, with an average of 154.745 tuna drift gillnet vessels per year in the ports of Karachi, Gwadar, and Pishukan. Authors urge caution of interpretation of results as the project is ongoing, with continued vessel counting, model verification, and an analysis of vessel length forthcoming.

Background

Roughly 2 billion people live along the Indian Ocean, where artisanal fisheries play important economic, cultural, and subsistence roles in the region (Anderson, 2014; WWF, 2020). A variety of gear types are fished in the region, but gillnets are the most common and comprise roughly 35 percent of nominal catches within the Indian Ocean Tuna Commission (IOTC)

Convention Area (Anderson et al., 2020; Aranda, 2017). Drift gillnets are relatively straightforward to set and retrieve, do not require bait, and can be operated cheaply (Anderson, 2014; Aranda, 2017). Thus, drift gillnets are an attractive and affordable 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, yellowfin tuna, skipjack tuna, kawakawa, longtail tuna, blue marlin, mackerel, and frigate tuna (Anderson 2014, Aranda 2017).

Under IOTC reporting requirements, most drift gillnet fisheries in the Indian Ocean are considered artisanal (Aranda, 2017; Kiszka et al., 2009), which poses a challenge for monitoring programs and results in significant knowledge gaps (Moore et al., 2010; Shester & Micheli, 2011). Vessel length overall (LOA) and area of operation are the factors that typically define vessels as artisanal or industrial in the IOTC (Aranda 2017). Specifically, industrial vessels are considered as those larger than 24 meters fishing on the high seas and in Exclusive Economic Zones (EEZs), as well as those under 24 m fishing on the high seas. Artisanal vessels are considered those under 24 m LOA fishing within EEZs (Moreno & Herrera, 2013). Moreno and Herrera (2013) proposed distinguishing a third classification of semi-industrial vessels for vessels between 15-24m LOA, and distinguishing artisanal as vessels less than 15m fishing in EEZs. 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 (Aranda, 2017).

This classification as important, as several IOTC conservation and management measures (CMMs) render vessels under 24 meters LOA fishing in their EEZs 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 '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).

Since 2000, roughly half of IOTC Members have reported drift gillnet catch for IOTC-managed fish species[1] (Table 1). From 2000-2020, the IOTC Members with the highest mean catch in gillnets overall were Iran, Pakistan, Indonesia, India, and Oman for both artisanal and industrial fisheries, respectively (IOTC 2022; Table 1).

Table 1: Mean annual catch for nations reporting drift gillnet catch for IOTC species from 2000-2020. Note: This table only refers to gillnet catch caught exclusively with drift gillnets (e.g. not with longlines attached to gillnets). Data accessed: November 2022.

[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 marline (*Makaira indica*), striped marlin (*Tetrapturus audax*), Indo-Pacific sailfish (*Istiophorus platypterus*), and swordfish (*Xiphias gladius*).

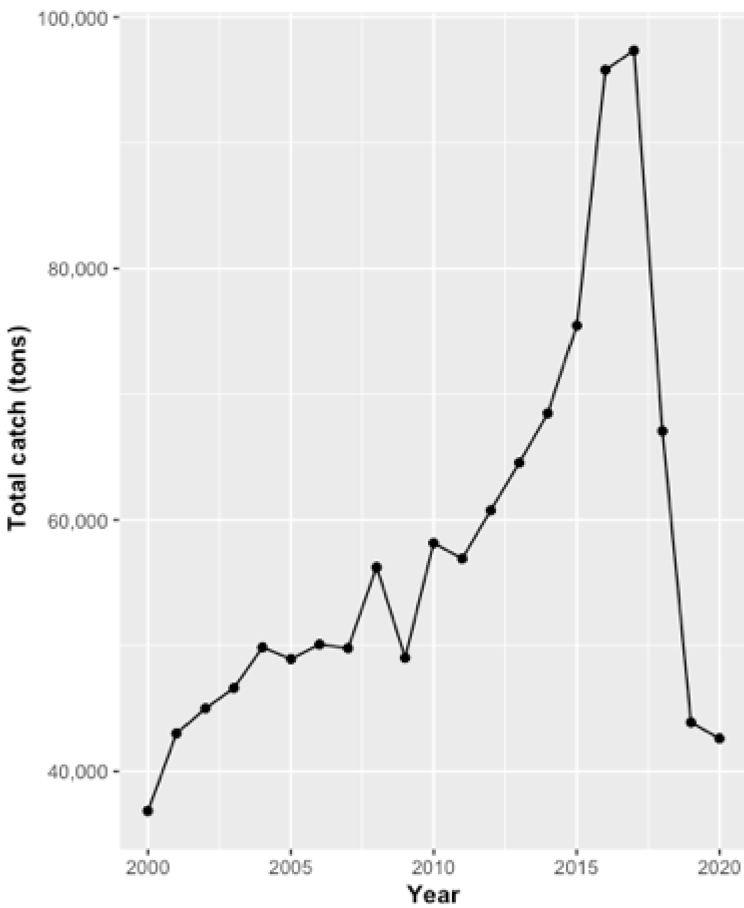
Fleet	Type of Drift Gillnet Fishery	Mean annual catch (tons)
Iran	Artisanal, Industrial	9,809
Pakistan	Artisanal	5,221
Indonesia	Artisanal	4,067
India	Artisanal	2,729
Myanmar*	Artisanal	1,771
Qatar*	Artisanal	588
Oman	Artisanal	1525
United Arab Emirates*	Artisanal	1382
Sri Lanka	Artisanal, Industrial	1311
Tanzania	Artisanal	882
Bangladesh	Artisanal	685
Saudi Arabia*	Artisanal	935
Malaysia	Artisanal	581
Thailand	Artisanal	185
Mozambique	Artisanal	285
Eritrea	Artisanal	134
Kenya	Artisanal	128
Kuwait*	Artisanal	100
Comoros	Artisanal	50
Bahrain*	Artisanal	4
Australia	Artisanal	0

*These countries are not IOTC Members, but the IOTC aggregates catch from FAO statistics to provide a full picture of gillnet catch in the IOTC Area of Competence.

Pakistan's Tuna Drift Gillnet Fishery

Pakistan is one of the top-five IOTC drift gillnet fishing nations in terms of mean landed catch volume (Table 1), and its tuna catch has been generally increasing over the past few decades until recent years (Figure 1). Pakistani gillnet fisheries landed an average total catch of 69336.20 tons of tuna in recent years (2015-2020) (IOTC 2022), though catches declined in 2018 and 2019 due to early closures, low catch, and warmer sea surface temperatures leading to jellyfish blooms (Khan 2021). Commercial landings in Pakistan consist of six tuna species, with nearly half the catch being yellowfin tuna, followed by longtail tuna, kawakawa, frigate tuna, skipjack, and bullet tuna (Nawaz & Moazzam, 2014). It is important to note that it is likely that Pakistan's gillnet catches are underrepresented, as issues with catch data have been reported dating back to the late 1980s (Anderson et al., 2020; IOTC 2019). The IOTC has reconstructed Pakistan's catch data, which are represented here (Figure 1).

Figure 1: Total Pakistani catch in tons/year in gillnet fisheries reported to the IOTC for the 16 IOTC-managed species from 2000-2020. Data accessed: November 2022.



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, and vessels used to transport fish but not actively fishing, make it challenging to quantify Pakistan's gillnet fleet (Khan, 2018). Many vessels also engage in gear switching, transitioning between gillnets and trawls depending on the season (WWF Pakistan, personal communication, 2022). The best information suggests that, as of 2017, roughly 700 pelagic tuna drift gillnet vessels operated in Pakistan, including 300 large tuna gillnet vessels between 15-25m LOA that catch tuna and tuna-like species and 400 smaller vessels (10-15m) operating in coastal waters, catching neritic tunas (Khan 2018; IOTC 2019). A few vessels of 40-45m LOA have been recorded (WWF Pakistan, personal communication), which have onboard freezing facilities. 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 meters in length or those under 24 m and fishing outside the respective EEZ.

Cetacean bycatch

In addition to widespread data gaps on catch statistics and fishing effort that is 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 these fisheries since 1950 (Anderson et al., 2020). Estimates of cetacean bycatch in Pakistani gillnet fisheries suggest that 8,411 (SE=1,057) cetaceans are taken annually as bycatch in surface gillnets (Kiszka et al. 2021); Anderson et al., 2020 estimated bycatch of 8,000 to 10,000 individuals per year for Pakistan. WWF Pakistan's drift gillnet mitigation efforts is the most comprehensive bycatch monitoring program known in the Indian Ocean and provides important insight into Pakistani fleet characterization and bycatch (Kiszka et al., 2021). Still, as is the case with all Arabian Sea fleets, information about fishing effort, catch, and bycatch is sparse.

Conservation Technology for Fisheries Monitoring

Current techniques to monitoring and managing fishing effort include monitoring via logbooks, onboard observers, fishermen 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 are not always available, particularly in artisanal fleets. Another conservation technology, namely very high resolution (VHR) satellite-based remote sensing, and its applications to the 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 predatory-prey relations, marine megafauna distribution (Corbane et al., 2010; Höschle et al., 2021), and inform ecosystem-based fisheries management (Chassot et al., 2011).

Currently, typically three types of satellite imagery sources are used in fisheries monitoring (outside the AIS context): 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 sub-meter spatial resolution, visible colors, and offers the best imagery (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 related applications of this technology (Elvidge et al., 2018; Hsu et al., 2019).

For optical VHR imagery, the WorldView-3 and 4 satellites offer the highest commercially-available spatial resolution 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). 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. Additionally, Google Earth offers free and readily accessible imagery for use at fine-scale digital elevations. 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).

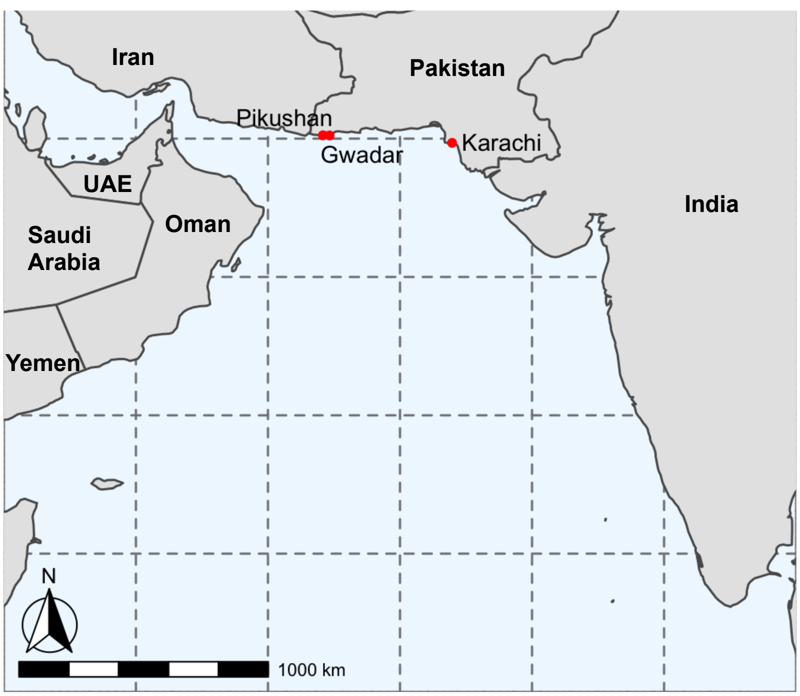
To better understand Indian Ocean tuna drift gillnet fleets, particularly those under 24m length overall that are not subject to IOTC reporting requirements, this study uses satellite imagery to estimate the number of Pakistani drift gillnet vessels in port and characterize the fleet. We selected Pakistan as a case study given the ongoing and dedicated monitoring of the gillnet fleet by WWF Pakistan, which has provided a dearth of information to supplement our satellite analysis. Our specific objectives are 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 on fishing grounds; 3) develop a transparent and transferable mixed-methods approach to obtain bycatch estimates in data-poor fisheries; and 4) determine if these estimates can inform revised bycatch estimates. We present preliminary results, noting that additional analyses are ongoing, such as the machine learning, calculation of model error and ground-truthing components.

Materials and Methods

Study Sites

We selected three fishing harbors in Pakistan as our 'study sites' for drift gillnet satellite imagery analysis: Karachi, Gwadar, and Pishukan (Figure 2). Based on personal communication with WWF Pakistan, these are the three primary ports in Pakistan for tuna drift gillnet vessels. Following consultation with WWF Pakistan on the primary areas in port where tuna drift gillnets dock with the highest density, we selected specific polygons to sample for analysis. In total, we reviewed three areas in Karachi, one in Gwadar, and two in Pishukan.

Figure 2. Location of three port study sites in Pakistan.



Satellite imagery

We reviewed all publicly available satellite imagery from Google Earth Pro from January 2021 to August 2022 ("the study period") that was available at 700 feet digital elevation. Image availability varied by location, and we sampled all available imagery in each location. Pishukan only had one month of imagery available out of the study period, and thus 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 (8192x5452 pixels). For each study polygon, we manually tiled satellite imagery at 700-750 feet digital elevation. In other words, for each polygon, we moved from left to right and top to down to sample imagery for the entire polygon. It was not possible to align the same digital elevation for each location, hence the flexibility to sample between 700-750 feet based on how far the analyst was able to zoom in per location.

Manual imagery annotation and analysis

Image annotation in objection detection is rapidly expanding, and there are multiple software tools available for image annotation. We selected BIIGLE 2.0 as our image annotation software, a web-based platform build for detection of objects of interest (OOI) in the marine environment (Langenkämper et al. 2017). Biigle offered an annotation feature particularly relevant to our study – the ability to rotate annotations – which was critical given the density and positioning of vessels. Here, we used rectangular boxes as our annotation feature.

To manually count OOIs in our study (i.e. gillnet vessels), we loaded each Google Earth Pro image into Biigle. We annotated every single vessel in the study polygons. If there was overlap of a vessel between two images, we took two approaches: For polygons 1 and 2 in Karachi, the vessel was assigned to be counted in the northern (top) polygon; for all other polygons, the vessel was counted in the image for which it showed more than 50 percent of the vessel.

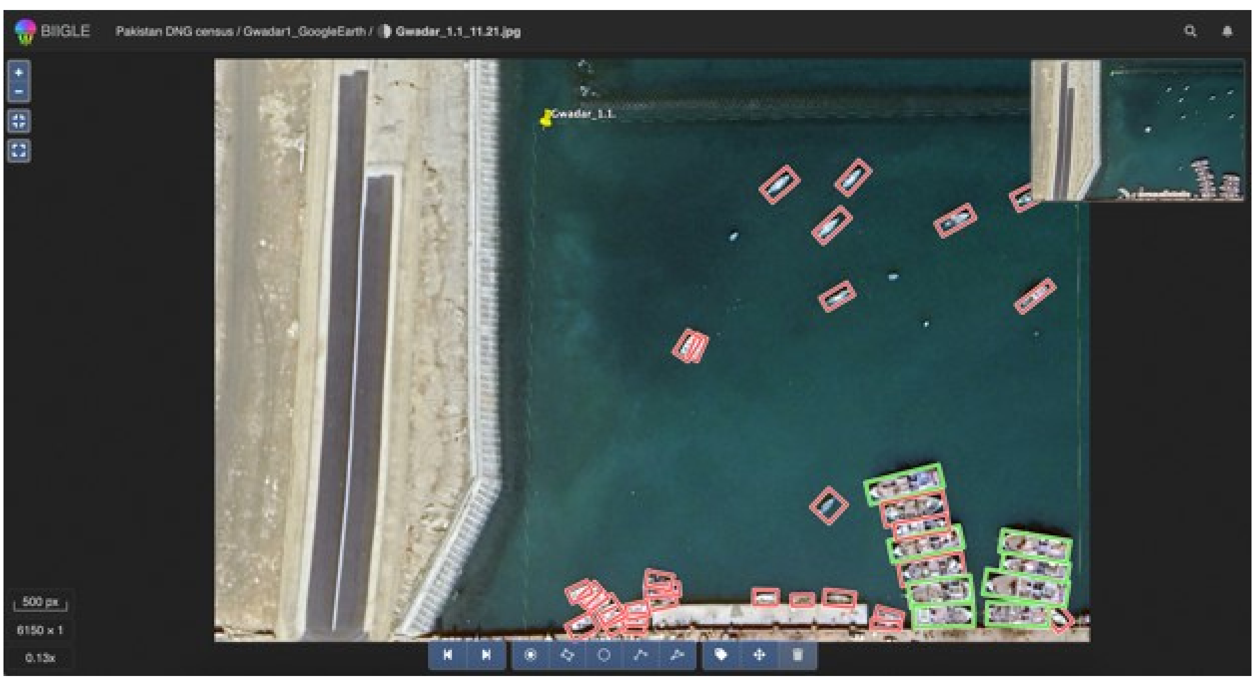
We used three categories for image annotation: "yes," "maybe," and "no" (Table 2, Figure 3). A vessel labeled as yes indicated that the analyst detected it to be a gillnet vessel; "maybe" referred to vessels that had the shape and other defining features of a tuna drift gillnet but could not definitively 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. Table 2 outlines defining features for each image annotation category. In the case of gillnet gear visible on board, the analyst drew an additional annotation for "gear present," but only in rare cases where it was easily visible.

Table 2. Criteria for three annotation classes.

Annotation category	Required criteria	Additional guiding criteria
Yes	Flat stern	Space between deck house and front of
	Pointed bow	

	Awning and/or deck house located at center/top center of vessel	vessel elevated (Karachi)
	Space between deck house and front of vessel	
	Vessel *not* one color	
Maybe	Flat stern	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.
	Pointed bow	
	Deck house	
No	Submerged, partially or fully	
	Pointed bow and stern or flat bow and stern	
	Definitively other types of vessels: katra, trawl, or other	
	Painted fully blue or red	

Figure 3. Example of image annotation in Biigle 2.0 for Gwadar in November 2021. Green boxes represent gillnet vessels; red vessels are not gillnets based on the criteria in Table 1.



Data Analysis

Once all vessels were annotated, data was exported from BIIGLE 2.0 as CSV files for each polygon for analysis in R Studio, version 2022.07.1. We calculated the total and average number of vessels over the entire study period and standard error by port, annotation class, and time; we calculated a sample of the average vessel length for a sample of vessels in Karachi, Gwadar, and Pishukan by using Google Earth Pro's ruler tool[2]; and we tallied the number of vessel labeled with a "gear present" annotation. We note that for Gwadar, there were several months where multiple images were available per month. For those months, we averaged the total vessels for repeat imagery in a month and used that as the overall count data for the analysis.

Results

Image coverage

A total of 489 Google Earth Pro images were reviewed for 2021-August 2022. Gwadar had the most images available, covering all but three months between 2021 and 2022 and often having multiple images available for some months (Table 3). This was followed by Karachi, and then Pishukan, which only had one image available at 700 feet digital elevation during the study period. December/January and June-October had the lowest image availability. Karachi had the highest spatial area sampled (2.36 km^2), followed by Pishukan (1.35 km^2), and lastly Gwadar (0.18 km^2).

Table 3. Google Earth Pro image availability from January 2021-August 2022

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					7
Karachi	2021	x	x	x		x	x			x	x			7
	2022		x	x	x	x								4
Pishukan	2021					x								1
	2018							x						1

Average and count data from Google Earth analysis

A total of 5648.25 boats were manually counted in this analysis for the two-year period. Gwadar had the most vessels in total (n=2791.25), followed by Karachi (2636.00), and Pishukan (221) across both years. Nearly two-thirds of vessels occurred in the "no" category (n=3410.25), followed by vessels labels with a yes (n=1565.67), and then vessels labeled as "maybe" (n=666.33) in both years. Karachi and Pishukan had more vessels in 2022 than 2021 for all annotation labels, even though 2022 had fewer images available for Karachi. For vessels annotated as "yes," there was an overall increase from 2021 (n=738.17) to 2022 (n=785.50).

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

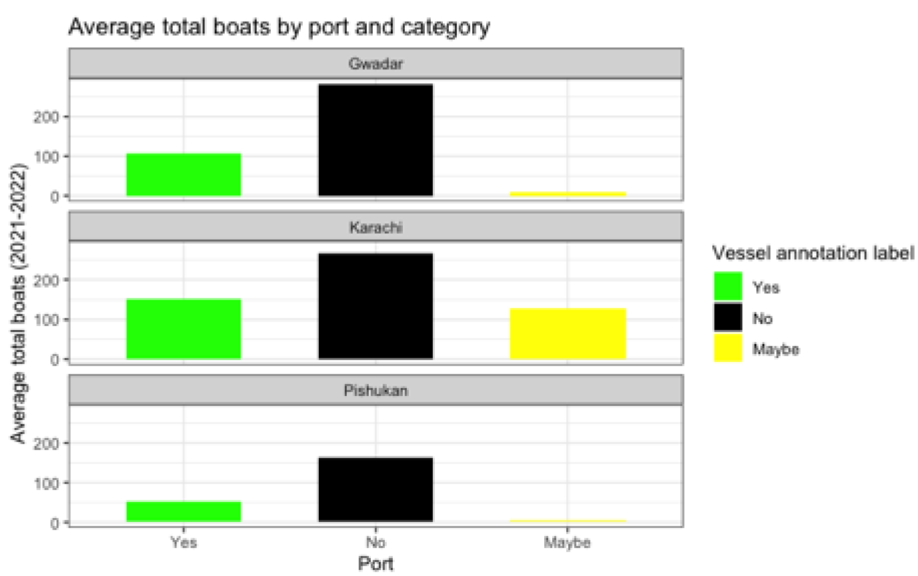
This translated to, on average, Karachi having the highest number of vessels overall on average (n=546.07), followed by Gwadar (n=398.31) and then Pishukan (n=221). The vessel counting for Karachi is 1) ongoing and 2) has three fewer months of image availability than Gwadar, so it is expected that the total and average number of vessels in Karachi will continue to increase. Overall, the image annotation category of "no" had the highest number of vessels overtime, with the "yes" category in the median with an average of 154.75 "yes" vessels between the two years.

In addition to detecting the number of gillnets, we also originally intended to annotate and look for the presence of gillnet gear on board. We found this challenging, often without high enough resolution to confidently detect it. Seven objects were detected as being gillnet gear – four in Karachi and three in Gwadar – but the authors do not find this reliable enough to warrant further investigation in this paper (Appendix I).

Table 4. Average notal number of boats

	2021			2022			Total boats
Port	**Yes**	**Maybe**	**No**	**Yes**	**Maybe**	**No**	
Gwadar	49.31	4.83	141.89	56.93	4.21	141.14	398.31
Karachi	98.25	96.50	201.75	54.00	30.14	65.43	546.07
Pishukan	42.00	0.00	71.00[3]	9.00	6.00	93.00	221
Total	189.56	101.33	414.64	119.93	40.35	299.57	1165.38

Figure 4. Average boats by port and category over the entire study period

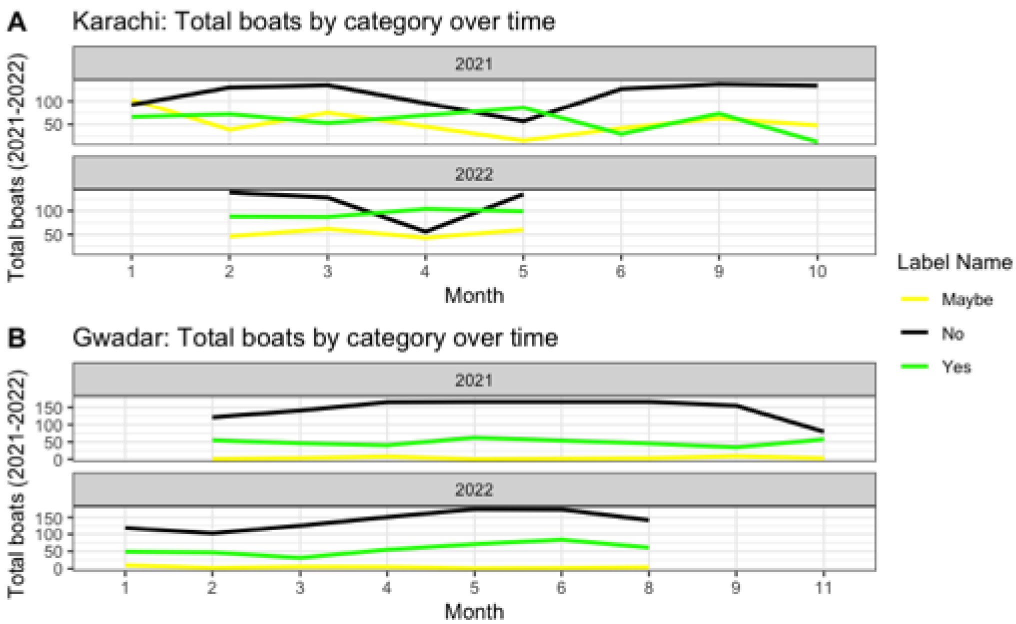


Temporal trends

[3] Pishukan values for 2021 actually represent July 2018 per image availability.

For all vessels, the top five dates with the highest number of counted boats overall were: March 2022, May 2022, September 2021, March 2021, and February 2022, respectively. This pattern generally held true for vessels in the “yes” category. For these vessels, the most boats were detected in May 2022, April 2022, May 2021, February 2022, and March 2022. The fewest vessels were detected in August 2021, July 2018, April 2021, June 2021, and October 2021. We note that for four of the highest-occurring vessel months, four of five had imagery available both Karachi and Gwadar in both years (Figure 5).

Figure 5. Total boats over time (note: count data, not average data)



Discussion

Vessel patterns

These preliminary results suggest that the Pakistani tuna drift gillnet fleet has at least 154.75 tuna drift gillnet vessels of the 15-24m LOA on average in recent years, with 152.25 vessels in Karachi, 106.24 in Gwadar, and 51 in Pishukan. However, the results presented here are preliminary, incomplete, and currently lack model verification, so we encourage caution with interpretation until the analysis is finalized. They are alos likely highly estimated, as they do not account for vessels in port across each month, and analysts took a conservative approach to counting a tuna gillnet vessel as a “yes;” it is likely that a portion of the vessels labeled as “maybe” are tuna drift gillnet vessels. Nevertheless, these results show a significant number of fishing vessels in the “semi-industrial” category that are not well documented by catch statistics or vessel registry at the IOTC.

By time and space, Karachi currently has the highest number of vessels, and that number is likely to increase as vessels in Karachi continue to be counted. Several seasonal patterns exist with tuna drift gillnet fishing in Pakistan: in August-December, more gillnetters fishing in coastal waters closer to Karachi to fish for white fish; from March-May, more gillnetters are offshore fishing for tuna; and from May-July, more vessels are in port during the rainy season (WWF personal communication). While we saw the highest number of vessels in Port in February, March, and May, results are too preliminary to draw conclusions at this point in time on seasonal patterns from our analysis. Given that more vessels stay in port during the monsoon season (roughly May-July), we expected more vessels to be in Port. However, image availability was missing from Google Earth Pro for those months, limiting the analysis.

Challenges and lessons learned

The work conducted so far for this project provides insight on a potentially promising way forward to better document poorly understood tuna drift gillnet fisheries. There are, however, several challenges to this work and early lessons learned. First, it was often challenging to decipher a tuna drift gillnet from a trawl vessel over satellite imagery in Karachi, where there are many gillnet and trawl vessels. These vessels have several features that look quite similar: similar vessel shape and length, and polls at the bow of the vessel. Indeed, these vessels may even engage in gear-switching, which exacerbates some of the similarities. From an eye-level view (Figure 6), it is easier to tease them apart; from a bird-level view, it was often challenging to decipher the type of vessel. In those instances, the analyst took a conservative approach and assigned the vessel as a “maybe.” This was more so a challenge in Karachi where there is more frequent mixing of trawl and gillnet vessels; Gwadar and Pishukan are more predictable with vessels being tuna drift gillnet vessels. We expect that forthcoming ground truthing will provide insight on the accuracy of vessel detection via satellite imagery.

Figure 6. Eye-level view of gillnetters and trawlers

Furthermore, image availability inconsistencies of Google Earth Pro, both within one Port area and across Ports, makes accurate and systematic estimates of the number of vessels challenging. It is also not georeferenced, which limits the potential of its analysis without adding in extra steps for post-processing georeferencing. At the same time, the free and open-access nature of Google Earth Pro makes it an incredibly powerful tool for such baseline analyses.

Assumptions

It is important to note that while this work adds context as to a preliminary vessel estimate, the estimates are 1) preliminary and 2) several assumptions have been made about this estimate. First, it assumes that a vessel counted as "yes" is actively fishing and 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 that may be 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 port at the time of screen capture. Finally, analyst error/fatigue exists with manual object detection, and a level of analyst error can be assumed.

Co-authors are currently investigating different statistical approaches to model these assumptions and calculate appropriate error. Furthermore, port-based ground-truthing is planned for the ports of Karachi and Gwadar, led by WWF Pakistan, which will provide further verification to these assumptions and annotated vessels.

Next steps

This project is a multi-staged project to better understand and characterize the Pakistani tuna drift gillnet fleet. The Google Earth Pro manual detection was the first stage to set a baseline understanding for the number of boats. Additional and ongoing work includes:

- *Machine learning:* Currently, project members are training models with the open-source tool, "FiftyOne," with the same imagery described here. Once that is complete, we hope to expand the temporal range of these estimates into earlier years, as well as compare the results provided by manual and automated detection.
- *Analysis of other high-resolution satellite imagery*: We are in the process of tasking the Worldview 3 and 4 satellites for additional imagery. Once that imagery is acquired, we will compare results across multiple imagery sources.
- *Ground-truthing:* In the coming weeks, WWF Pakistan will commence ground truthing in the ports of Gwadar and Karachi to verify a sample of annotated imagery. This will help inform standard error of these estimates.
- *Bycatch estimates:* Ultimately, we aim to continue to provide information on cetacean bycatch estimates. Leveraging existing data from WWF Pakistan collected during their crew-based observer program alongside port-based surveys as part of this study, we hope to make extrapolated bycatch estimates.

Implications

This work sheds light on the tuna drift gillnet fleet in Pakistan, for which accurate reporting and statistics at both the national and IOTC level does not exist for vessels detected in this study of 15-24m LOA. Due to their size, these vessels are not on the IOTC Vessel Registry. This represents significant data gaps for tuna drift gillnet vessels fishing for tuna in the IOTC

Convention Area, warranting further discussion on the classification of vessels between 15-25m LOA.

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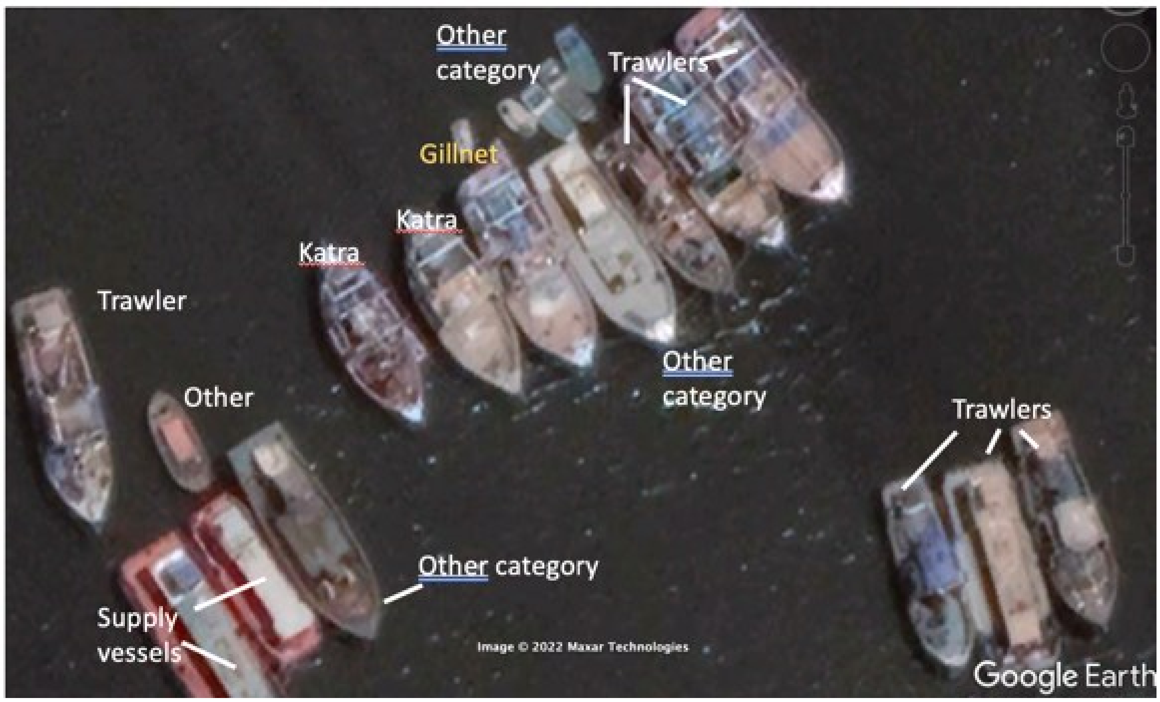
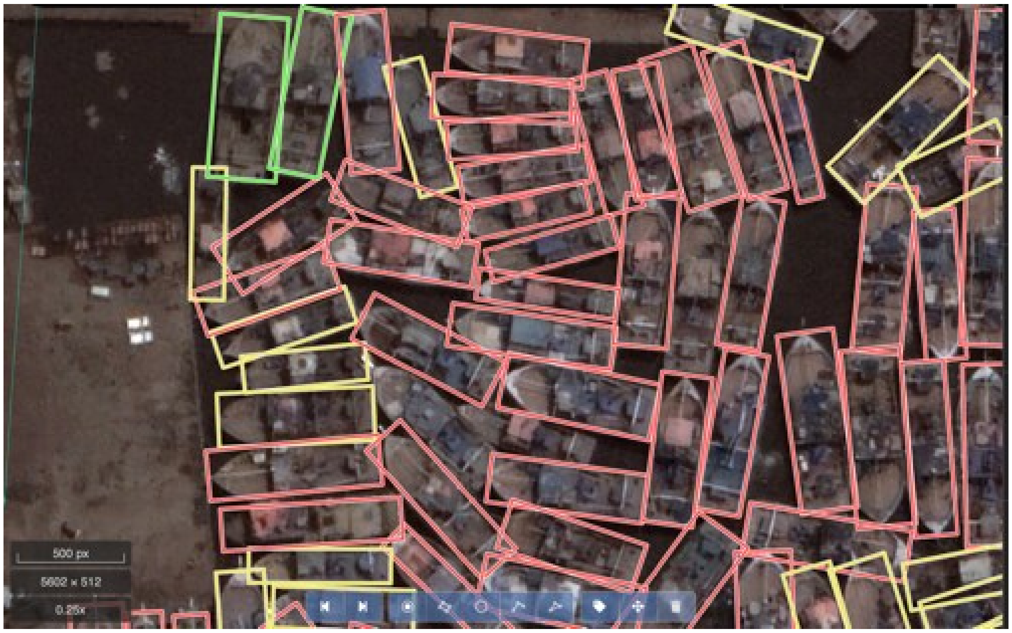
Appendix A: Examples of annotated images

A.1. Labeling example of several different vessel types in Karachi



A.2. Example of annotated image in Karachi, April 2022. 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.



A.3. Example of detectable gillnet gear on board (circled) in Karachi, February 2021.