

# Measuring Artisanal Fisheries Using Remote Sensing

## A Deep-Learning Model Piloted in Hadramawt

Olivier Ecker, Zhe Guo, Hanxi Li, and Liping Di

### Key Findings

An innovative remote sensing study piloted in two sites (Mukalla and Qusayir) in Hadramawt Governorate, Yemen, reveals the following key findings:

- Deep learning using very high resolution satellite imagery can accurately detect small artisanal fishing boats.
- The YOLO11 Oriented Bounding Boxes model performs best, with an overall accuracy of 96.9 percent, and enables measuring boat size and identifying boat types.
- Mukalla's fleet numbered around 800 operational boats in 2021–2024, most of which were *houris*, while *sanbuqs* accounted for 6.9 percent. Qusayir's fleet numbered 450 boats, all of which were *houris*.
- The composition of the combined Mukalla and Qusayir fleets by boat type and length class is similar to the composition of Hadramawt's entire fleet, as shown by a recent landing site survey.
- Approximated fish-catch capacities of the Mukalla and Qusayir fleets indicate that current boat sizes are not a notable constraint to increasing the productivity of these artisanal fisheries.
- The proposed remote sensing approach is an important first step toward development of a cost-effective tool for monitoring and analyzing artisanal fishing activities in Southern Yemen and beyond.

Artisanal fisheries dominate the fishing sectors in many developing countries. In Yemen, artisanal fisheries are thought to account for more than 90 percent of total fish production (Impact Consulting, 2022). The country has a mainland shoreline of more than 2,200 km, two-thirds of which are the Gulf of Aden and Arabian Sea coasts. Yemen was a major regional player in fisheries before the recent conflict erupted in 2014. Fisheries were the country's second-largest export sector, contributing about 3 percent to national GDP (World Bank, 2025). However, years of conflict and lack of maintenance have left fishing boats and fisheries infrastructure destroyed, damaged, or dysfunctional at many landing sites. Fish

production has also suffered from high fuel prices and apparently declining fish stocks due to lack of regulations and enforcement (Apex & AAMS, 2025; Belton et al., 2026), including against illegal commercial fishing activities by foreign country vessels in Southern Yemen’s territorial waters (GFW, 2020). Overfishing of some species is reportedly widespread, threatening the catch of artisanal fishers (Ali et al. 2024). However, accurate and up-to-date data on the impact of the conflict on artisanal fisheries, the magnitude of legal and illegal fishing activities, and the size and health of fish stocks in Southern Yemen and its territorial waters are not available.

Artisanal fisheries have been identified as a key sector for interventions to support postwar economic recovery and livelihoods in coastal communities, especially in Southern Yemen (UNDP, 2024). The number of artisanal fishers on the Gulf of Aden and Arabian Sea coasts (hereafter only “Gulf of Aden coast” for brevity) was estimated to be more than 37,000 in 2018 but is likely significantly higher today, with recent estimates ranging up to 96,000 fishers (Apex & AAMS, 2025). Across Yemen, fish is also an important part of household diets and crucial for food security. It is the second most frequently consumed animal-source food after dairy and an essential source of high-quality protein, omega-3 fatty acids, and micronutrients (Dey et al., 2026). Fish consumption is critical for reducing nutritional deficiencies, especially among children living in poor food environments, common in many parts of Yemen, where it is difficult to obtain enough essential nutrients from a variety of foods (Robinson et al., 2022; Kawarazuka & Bene, 2011).

While reliable official statistics on current fish production volumes and growth potentials are lacking, most recent estimates suggest that Yemen’s total fish production was about 151,000 metric tons (mt) in 2023—down from 229,000 mt a decade earlier (FAO, 2026). The Gulf of Aden is thought to provide an estimated 65 to 70 percent of total fish production (Impact Consulting, 2022). Disaggregated production data by administrative areas or landing sites are very incomplete, impeding assessments of the contribution of artisanal fisheries to the local economy, coastal livelihoods, and food security. Where statistics are available from local fisheries authorities, fish production is likely underreported, due in part to the fees and levies that fishers are obliged to pay based on their declared catch and sale values (Alabsi & Komatsu, 2014). Anecdotal evidence also points to unrecorded fish landings at unofficial landing sites and at-sea transfers of catch, including onto foreign commercial fishing vessels (Belton et al., 2026).

Accurately measuring artisanal fisheries by coastal region and landing site is a fundamental first step for establishing fisheries monitoring and information systems, developing fishery sector and economic policies, optimizing donor-funded support projects, and implementing effective regulations for sustainable harvesting of fish resources. Key basic parameters are the size and composition of the operational local fishing fleets—data which also enable inferences about fishing capacities. The first comprehensive survey of landing sites along the Gulf of Aden coast carried out after the recent conflict was in 2025 by Apex Consulting and Advance Africa Management Services (Apex & AAMS, 2025). The survey data provide a much-needed profile of artisanal fisheries in Southern Yemen at present and a baseline for future assessments of sector development. Main indicators measured at all surveyed landing sites include counts of active fishing boats, boat length measurements, and fish hold capacities. While this survey provides a valuable snapshot of the current state of artisanal fisheries, it falls short of examining fisheries dynamics, including declining fishing activities (due to depleting fish stocks or increasing fuel prices, for example), changing fleet size and composition (due to modernization, for example), and shifting seasonal fishing patterns (resulting from climate change, for example). Monitoring these changes over time and across space requires a longitudinal study design with a high level of spatial disaggregation, which is quite expensive if based on primary data collection.

In this study, we propose a new remote sensing approach that uses very high resolution (VHR) satellite imagery and machine learning to detect artisanal fishing boats, estimate their dimensions, and track artisanal fishing activities over time. Specifically, deep learning—a specialized subset of machine learning that uses multilayered artificial neural networks to automatically learn complex patterns from large amounts of data—is employed. We developed and tested a deep-learning model using remote sensing data from our primary study site in Mukalla and then applied the best-performing model variant to data from Mukalla and our secondary study site in Qusayir. Both sites are located in Hadramawt Governorate in Southern Yemen. We demonstrate that boat count and dimension measurements can be used to gain information about fleet size and composition by boat type and length class and approximate fishing capacities. We validate our approach by comparing our modeled estimates with estimates from the recent landing site survey. A strength of our approach is that it can be scaled and transferred at relatively low cost, and therefore offers a promising basis for developing an artisanal fisheries information and monitoring tool.

## Study sites

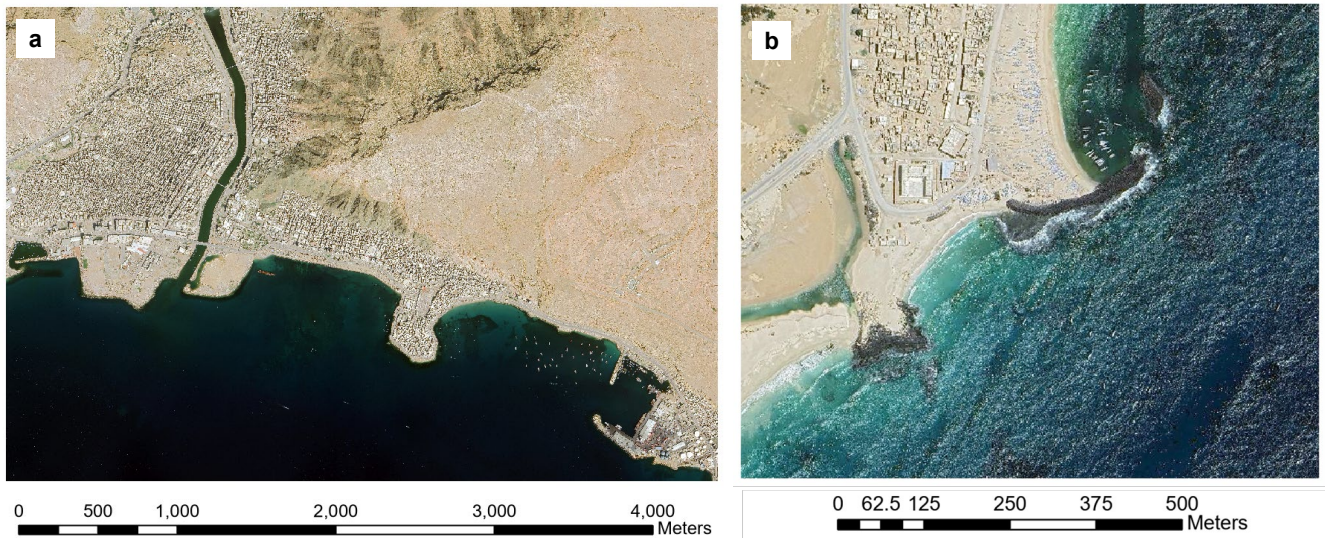
The primary study site is the shoreline of and water channel in the city of Mukalla (Figure 1a), which is the capital of Hadramawt Governorate and a major fishing hub in Southern Yemen. It has a relatively large port area that includes protected fishing boat landing sites, such as in the city's fisheries and industrial ports and the channel, and several semi-protected anchoring areas in rock-fortified shoreline bays. The secondary study site is the only landing site in the town of Qusayir in Hadramawt Governorate (Figure 1b) and is much smaller than the primary study site. Qusayir is located about 150 km east of Mukalla in a rural area; the coastal town of Ash Shir—another major fisheries hub—lies about halfway in between. There is a short breakwater to protect a small anchoring area from a rough sea. Unlike in Mukalla, most fishing boats (particularly small vessels) in Qusayir are pulled out of the water after each fishing trip and placed closely together on the beach, as the anchoring area is too small for the entire fleet of Qusayir (and is reserved for larger vessels).

We selected the landing sites so as to capture a range of diverse features of landing sites along the Gulf of Aden coast and, at the same time, to focus on the more important ones. Based on reported boat counts, artisanal fishing activities are concentrated in the easternmost region of Southern Yemen. Landing sites in Hadramawt and Al-Maharah Governorates are the bases of almost 60 percent of the Gulf of Aden artisanal fishing fleet (Apex & AAMS, 2025). Most boats land in Hadramawt Governorate (30.7 percent). *Sanbuqs*—a boat type that is larger and much less common than the dominant *houris*—were recorded exclusively in these two governorates in the landing site survey, and almost all land their catch in Hadramawt (97.6 percent) (Apex & AAMS, 2025).<sup>1</sup> Mukalla and Ash Shihr are the two major fisheries hubs in the Hadramawt Governorate. These two locations, together with the deep-sea port city of Aden, Ras Alaraa in Lahj Governorate on the Strait of Mandeb (which connects the Red Sea to the Gulf of Aden), and the easternmost city of Al Ghaydhah in Al-Maharah Governorate bordering Oman, are the main centers of Southern Yemen's fishing industry. Qusayir is a typical artisanal fisheries node, where fishing is vital to the local economy. Both Mukalla and Qusayir have essential infrastructure to support the artisanal fisheries value chain, including ice plants, auction yards, and cold storage. However, only Mukalla has industrial fish cleaning, processing, and canning plants, including for fish exports.

---

<sup>1</sup> The boat types are described below in greater detail.

**Figure 1:** Satellite view of the study sites in (a) Mukalla and (b) Qusayir



## Satellite imagery

Detecting artisanal fishing boats from space requires VHR imagery, that is, imagery with a spatial resolution of 50 centimeters (cm) or less. Any image consists of unicolored pixels, and different pixel shadings produce a visible picture. The smaller the pixels, the sharper the image. VHR imagery is required because of the long distance between a satellite in orbit and the Earth's surface, and the relatively tiny size of artisanal fishing boats. The imagery for our study was obtained from Google Maps, which processes images from different VHR imagery satellite systems (including the WorldView and Pleiades systems series). The pixel size of the images we used was less than 30 cm for both Mukalla (15–20 cm) and Qusayir (28 cm).

Satellites from these satellite systems all orbit over Yemen between 7 a.m. and 8 a.m. UCT, or 10 a.m. and 11 a.m. local time, which is a good moment to capture images of the boats. At this hour, most fishing crews have completed their fishing activities, so the fishing boats are already at their landing site or close to shore when the satellites pass. Fishers usually land their catch before consumer marketplaces and fish auctions open in the morning, and insulated trucks load fish for transport to inland markets or for export. Most fishers, relying on small *hour*i boats, undertake trips of less than one day and go out daily during the main fishing seasons. According to landing site survey data by Apex and AAMS (2025), 26 percent of all *hour*i-based fishing trips last less than 6 hours, and another 46 percent of trips last 6 to 12 hours. Typically, only fishing trips on *sanbuqs* last more than two days (mostly between 10 and 20 days), and *sanbuqs* also arrive at their landing sites usually before fish market and shipping activities start in the morning. The main fishing season runs from October to May, and fishing decreases when the monsoon season begins in June, bringing strong winds and rough seas that are especially perilous for small vessels.

The observation period of our study spans from 2021 to 2024. No VHR images of the study sites are available from Google Maps before 2021. There are five VHR images for Mukalla, taken in early November 2021, late October 2022, early May 2023, mid-June 2023, and early April 2024, and one VHR image from Qusayir, taken in mid-April 2023. The image of Mukalla from mid-June 2023 was used for

model training and testing purposes but later excluded from the analysis. The boat count from this image was significantly lower than those from all four other images (by 17–36 percent), with two semi-protected anchoring areas used by many *houris* in the main fishing season appearing almost empty. These boats were likely moved to more protected landing sites or pulled out of the water to prevent loss and damage during the monsoon season, removing them from the mid-June image.

## Boat detection

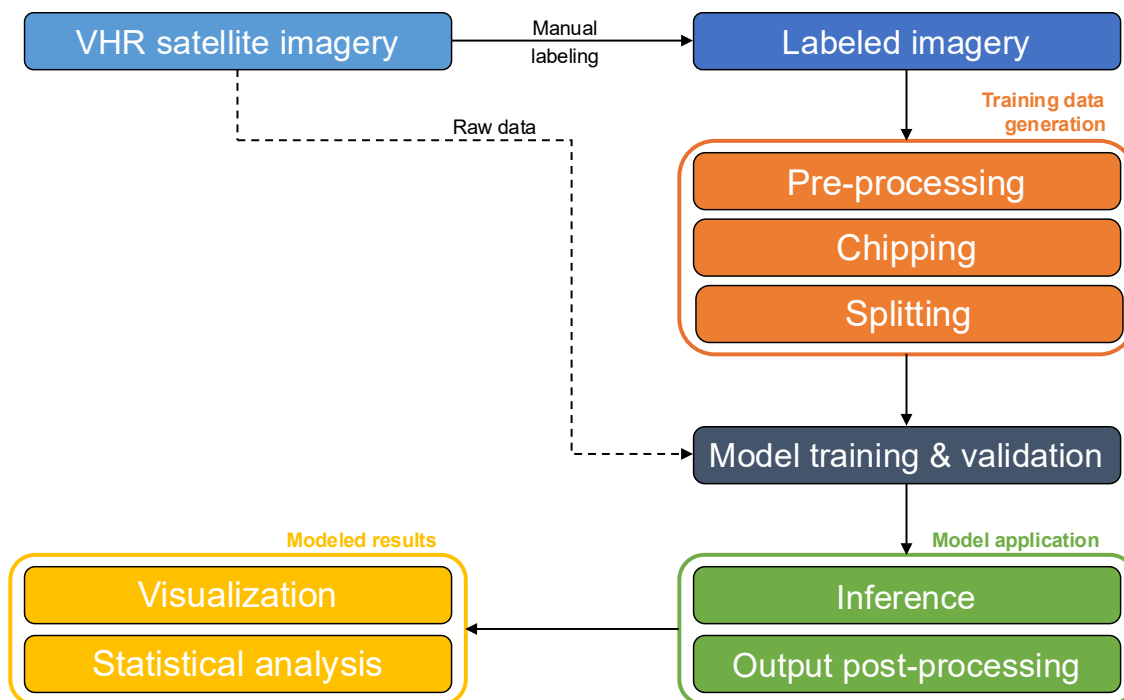
Remote sensing object detection using machine learning has recently advanced rapidly. Various methods of object detection can be applied to VHR imagery, but maritime applications for small targets (like artisanal fishing boats) and with complex background features (such as beaches, sea with whitecaps, and bow waves of moving boats) require particularly careful method selection and testing (Magalhaes et al., 2025). For this study, we selected Version 11 of the You Only Look Once (YOLO) model series. YOLO is a state-of-the-art real-time object detection framework that is used extensively with satellite imagery, including for identification of object features (Redmon et al., 2016; Bochkovskiy et al., 2020). Unlike traditional methods that scan an image multiple times, YOLO processes the entire image just once (that is, one-stage detection); it optimizes speed and accuracy in object detection. YOLO version 11 (YOLO11) introduces improved efficiency features and refined architectural designs that allow users to choose from different, high-performance object detection algorithms.

Using the five images of the primary study site (Mukalla), we developed and tested three YOLO11 model variants suitable for small object detection: Object Detection ('Detect'), Oriented Bounding Boxes (OBB), and Instance Segmentation ('Seg'). Detect is a standard model designed primarily to count objects and identify their locations. It draws rectangular boxes around detected objects only in vertical-horizontal orientation of an image. The OBB model is an advanced variant that draws rotated rectangular boxes around the objects that match each object's orientation. This is especially useful for accurately identifying boats in crowded landing sites, where artisanal fishing boats often have different orientations as several boats are tied together or onto a central anchor point, as well as for estimating boat length and beam (that is, a boat's width at its widest point). The Seg model draws a line around an object's shape. This is useful for detailed object mapping but is more computationally intensive. Moreover, dimensions of very small objects with no rectangular shape (like artisanal fishing boats), where the object area on an image consists of only a few pixels, might be measured imprecisely, as the line is drawn along pixel boundaries. Because we aim to measure boat length and beam in addition to counting boats, our preferred model is either the OBB or Seg variant, if its performance in boat detection is not significantly lower than that of the Detect model.

As we use a YOLO11 model, we expected relatively high boat detection efficiency for all three model variants, including for beach landings. While fishing boats in Yemen were traditionally constructed from wood, almost all operational boats today (more than 99.9 percent of the Gulf of Aden fleet) are made from fiberglass (Apex & AAMS, 2025). Fiberglass objects tend to be detected better than wooden objects because of a greater difference in the reflection of sunlight between object and background, especially on light sandy backgrounds. We also use the information about the construction material of operational boats, together with the placement of boats, in our object labeling on images. For example, boats in beach landing sites—especially when apparently made of wood and placed further away from the waterline than other boats, found in parallel orientation to the waterline (which is impractical for pulling boats into the water), or piled up on a particular spot—can safely be ignored in the target object labeling, excluding them from the count of operational boats.

Figure 2 depicts the workflow of our boat detection methodology. The steps are identical for all model variants, which ensures a fair comparison of their performance. Starting with the raw optical satellite images of Mukalla, we randomly selected a subset of images from which we generated labeled datasets used for developing the deep-learning model. First, we manually labeled and annotated the selected images to mark artisanal fishing boats. Second, we executed pre-processing operations to ensure spatial consistency between the raw satellite imagery and the labels and annotations on the edited images. These include reprojection and band combination so that the subset of labeled data can be accurately matched to all raw datasets within the same coordinate system. Third, imagery chipping was executed. Chipping divides the pre-processed images and corresponding labels into many small imagery tiles to facilitate the data processing in the YOLO11 model series and increase model accuracy in detecting small objects. Fourth, the chippings were randomly divided into two sets: a training dataset, used to teach the deep-learning model what boats look like, and a validation dataset, used to check how well the trained model performs. Fifth, once model performance in the validation dataset was acceptable, we applied the model to all images of Mukalla and the image of Qusayir to automatically detect artisanal fishing boats. Last, the model outputs were post-processed by converting them from YOLO11 format to formats for use in Geographic Information System (GIS) and statistical analysis software packages. The YOLO11-OBb model outputs include georeferenced object bounding boxes and geographic orientations of detected boats, as well as boat counts and estimated boat lengths and beams that we use for further analysis.

**Figure 2:** Boat detection methodology workflow



## Model performance and validation

The performance of all three YOLO11 model variants is high (Table 1), confirming the suitability of our deep-learning-based remote sensing approach for detecting operational artisanal fishing boats in landing sites in Hadramawt. The OBB model performs best. Based on VHR satellite images of Mukalla (Figure 3), the overall accuracy of the OBB model is 96.9 percent, with a correct identification of artisanal fishing boats ('precision') of 97.4 percent and a detection efficiency of all artisanal fishing boats ('recall') of 93.5 percent (Table 1). Thus, 96.9 percent of the artisanal fishing boats shown on an image that are operational (as per our labeling) are correctly detected as such, factoring in other objects incorrectly identified as artisanal fishing boats. The OBB model performs better than the other two model variants on all performance indicators. The recall performance indicator estimates show that the Detect model and especially the Seg model are both distinctly less efficient in detecting boats than the OBB model. The differences in the precision performance indicator estimates between the model variants are smaller, but still favor the OBB model. Consequently, the OBB model is our preferred model variant and is used in the analysis that follows. The OBB model is also the variant that allows us to estimate boat length and beam.<sup>2</sup>

**Table 1:** Performance comparison of YOLO11 model variants

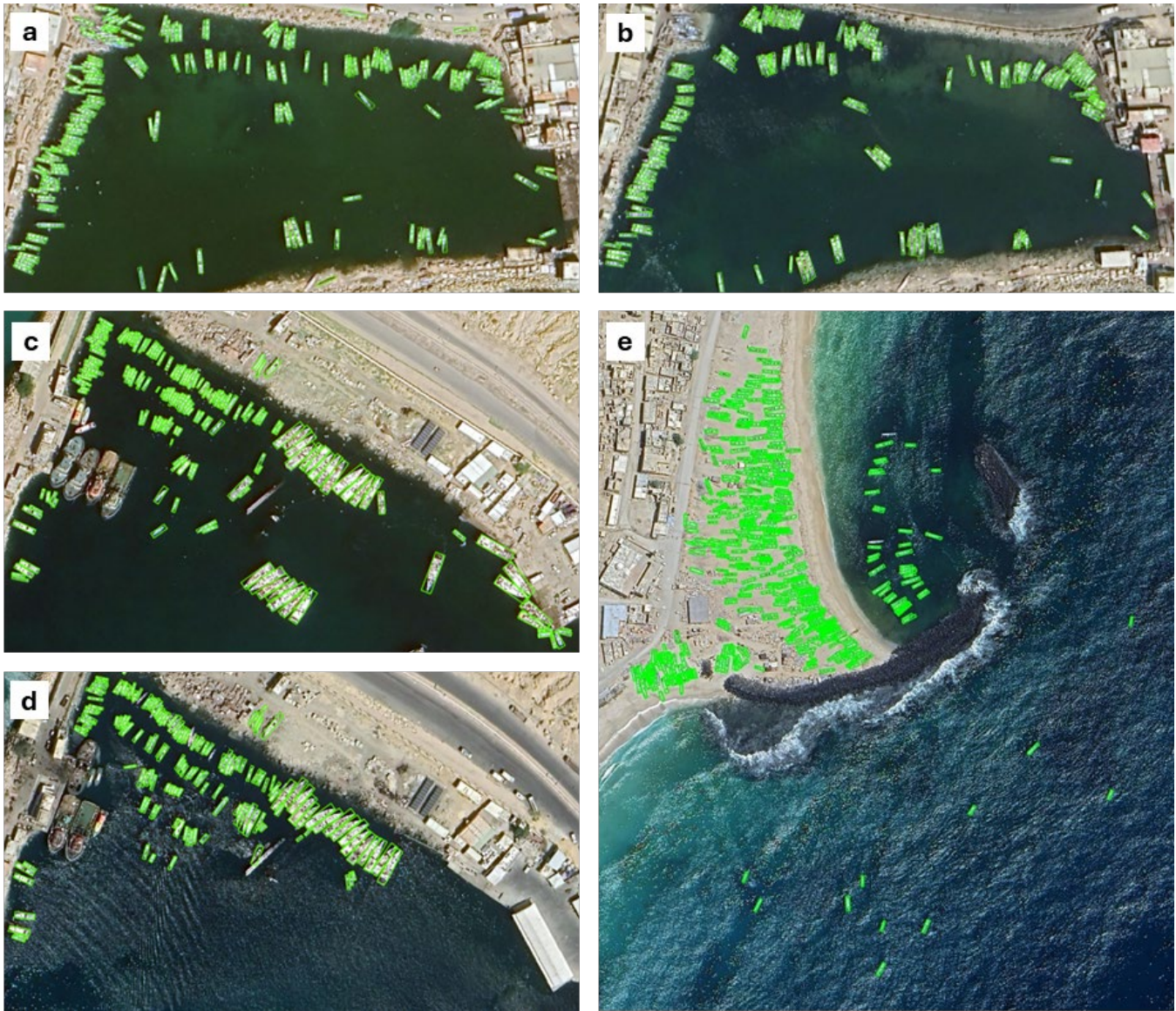
Model	mAP@50	Precision	Recall	Number of parameters (million)
Detect	0.9557	0.9603	0.9174	20.05
OBB	0.9686	0.9743	0.9351	22.36
Seg	0.9412	0.9565	0.8868	20.90

Note: mAP@50 = mean Average Precision at an IoU (Intersection over Union) threshold of 0.50 and above; precision = proportion of predicted boat detections that are actually correct; recall = proportion of actual boats in the validation data that the model successfully detects.

The images in Figure 3 illustrate the boat detection results of the YOLO11-OBB model, and highlight the model's strong performance: The detection picks up nearly all artisanal fishing boats that appear to be in use. It successfully differentiates artisanal fishing boats from—and therefore does not pick up—commercial fishing and cargo vessels, motorboats, trucks, buses, cars, buildings, and other objects that have similar shape or are made from materials with similar sunlight reflection patterns (Figures 3a and 3b). The model also performs well in separating boats in the water that are tied together or on land that are placed very close to each other. Certainly, boats are harder to detect on land than in the water. The model still handles substantially different landing site features and boat backgrounds well in its predictions, as visual comparisons of the images of Mukalla and Qusayir reveal (Figures 3a–c). Even under rougher sea conditions, model performance seems to be satisfactory, as it usually does not misidentify whitecaps as fishing boats. Important for boat size measurements, the object bounding boxes appear to be tightly drawn around boat bodies, and their angles of rotation closely match the boats' orientation.

<sup>2</sup> Post-estimation, we dropped 22 outlier observations, accounting for 0.5 percent of the pooled boat sample that includes observations from the four images of Mukalla and the image of Qusayir. We classify observations as outliers if boat length is below 3 meters—the minimum boat length found in the landing site survey (Apex & AAMS, 2025), or boats' length-to-beam ratio shows extreme values of above 8.5.

**Figure 3:** Examples of boat detection results from Mukalla and Qusayir



Note: The satellite images show the artisanal fisheries port in Mukalla in (a) November 2021 and (b) April 2024, a landing site for artisanal fishing boats in the commercial port in Mukalla in (c) November 2021 and (d) April 2024, and (e) the landing site in Qusayir in April 2023. The artisanal fisheries port is located on the west side of Mukalla's port area, and the commercial port on the east side (see Figure 1a).

To further validate and ground-truth our deep-learning model, we compare the modeled estimates with results from the landing site survey, provided in the artisanal fisheries profile report by Apex and AAMS (2025).<sup>3</sup> The survey was funded by the World Bank under the Sustainable Fishery Development in the Red Sea and Gulf of Aden (SFISH) program. On the Gulf of Aden coast, 60 landing sites, spread over all six coastal governorates of Southern Yemen (Lahj, Aden, Abyan, Shabwah, Hadramawt, and Al Maharah), were surveyed. Primary data were collected from June 2024 to March 2025, including the 2024 monsoon season and 2024/25 main fishing season.

<sup>3</sup> We use estimates as presented in tables and figures of the report (Apex & AAMS, 2025) rather than the underlying survey data directly (because the data were not made available at the time of this analysis).

## Boat count

The YOLO11-OBB model results suggest that the boat count of Mukalla’s artisanal fishing fleet varied between 709 and 914 operational boats during the 2021–2024 period (Table 2), with an average count of 800 boats. The number of boats significantly declined from 2021 to 2023, and slightly increased to 2024. Yet the trend implied by the observed year-by-year change should be interpreted with some caution, as the 2021 and 2022 images were taken at the start of the main fishing season, and the 2023 and 2024 images at season end, and so may not reflect a precise season average. The landing site survey finds a much lower boat count of about 540 boats in Mukalla (Apex & AAMS, 2025). This is closer to our modeled count from the excluded off-season image. It is not clear when the sites were visited during the survey period spanning from June 2024 to March 2025, or how well Mukalla’s extensive port area was covered. In a supplementary analysis, Apex and AAMS (2025) also provide a satellite imagery-based count for Mukalla of 832 boats in April 2024. This is 70 boats above our count and more than 50 percent above the report’s survey-based count. The modeled count by Apex and AAMS and our own for that month are based on the same satellite image, while the accuracy of our model is likely to be significantly higher as we use a more advanced methodology. Our total boat counts for Mukalla include between 557 *houris* in May 2023 and 669 *houris* in November 2021 that were in the water at the time the satellite images were taken. The average share of boats on land across the four images of Mukalla is 24.1 percent.

Our modeled results for Qusayir reveal a total boat count of 450 in April 2023 (Table 2). This is lower than the survey-based count of about 660 boats, while, again, the date of the Apex and AAMS landing site visit is not reported. Apex’s and AAMS’ satellite imagery-based count for April 2023 appears implausibly high, with 1,073 boats. This probable overestimation is possibly caused by poor model accuracy associated with misclassification of whitecaps as fishing boats, for example, or double-counting of boats on the beach squeezed next to each other, which is a common error when bounding boxes are not aligned with the orientation of an object and therefore drawn loosely around the shape of an object or parts of it. Our modeled results suggest that, unlike in Mukalla, most boats in the Qusayir fleet are landed on the beach, accounting for 87.6 percent of the total boat count. This finding was confirmed by key informants from Qusayir.

**Table 2:** Boat count by location and satellite image

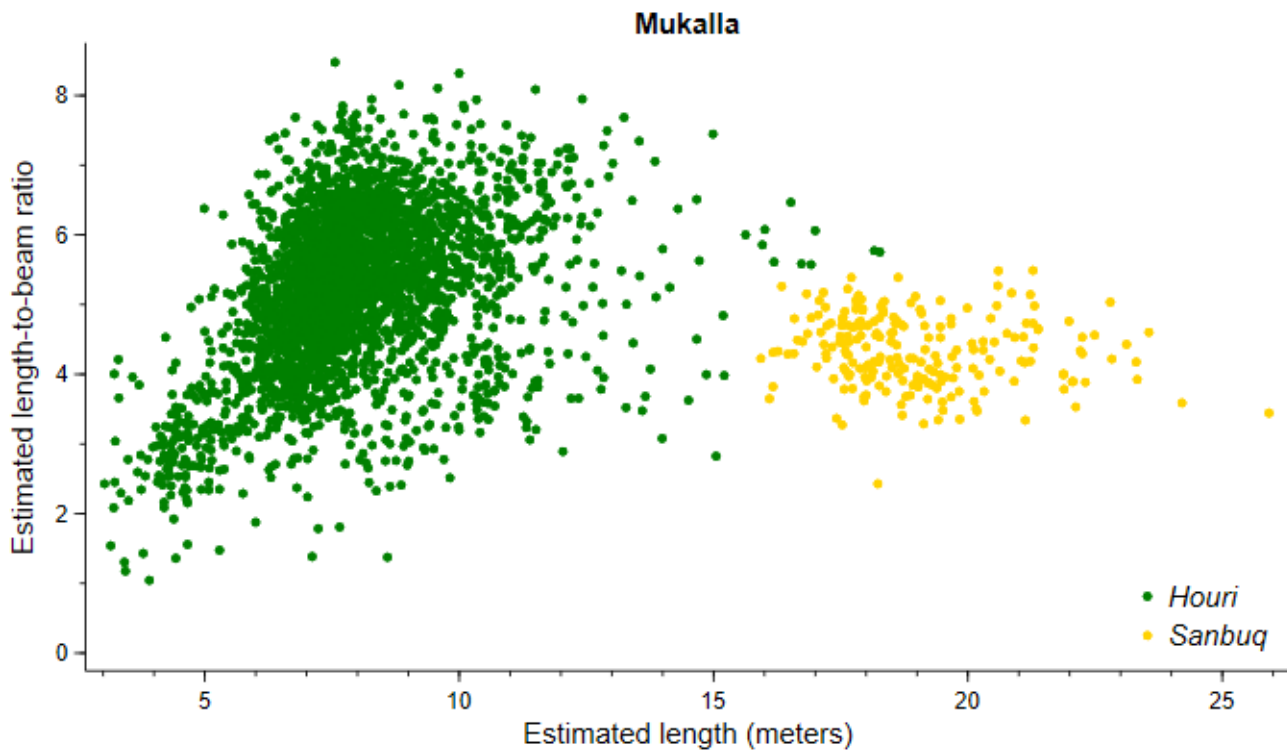
Location	Image date	Boat count			Share of <i>houris</i> on shore
		Total	<i>Houri</i>	<i>Sanbuq</i>	
Mukalla	6 Nov 2021	914	846	68	26.8%
	25 Oct 2022	816	766	50	22.7%
	6 May 2023	709	665	44	21.5%
	3 Apr 2024	762	706	56	25.2%
	<i>Average</i>	<i>800</i>	<i>746</i>	<i>55</i>	<i>24.1%</i>
Qusayir	15 Apr 2023	450	450	0	87.6%

## Boat type

Yemen's artisanal fishing fleet primarily consist of two boat types: *houris* and *sanbuqs*. *Houris* are the most common. These traditional open boats are long and narrow, designed for good operability in shallow waters, high maneuverability, and high speed. *Houris* generally range in length from 4 to 12 meters (m) and are equipped with a single outboard engine or, in some cases, a twin outboard engine. Because of their shape and lightweight profile, *houris* can operate from beach landing sites. They are ideally suited for inshore fishing and mostly used for short day trips only. *Sanbuqs* are longer and significantly wider vessels than *houris*, generally ranging from 10 to 25 m in length; hence they tend to have a smaller length-to-beam ration (LBR). They have large storage capacity, often have superstructure, and are powered by an inboard engine. *Sanbuqs* are used for offshore fishing on multi-day trips.

To classify out sample of boats by vessel type, we utilized the estimated boat length from our YOLO11-OBB model in combination with the estimated LBR. Boat length is measured with lower margins of error than boat beam. Because the beam of any (monohull) boat is shorter than its length, misidentification of pixels (that is, pixels detected as part of the object rather than the background, for example) results in larger relative deviations from the vessel's true beam than occur for vessel length. We consider this uncertainty and the fact that no *sanbuq* under 11 m was found across all landing sites surveyed by Apex and AAMS (2025). Specifically, to categorize detected boats into *houris* and *sanbuqs*, we pool observations from the four images of Mukalla and identify joint natural breaks in the boat length and LBR distributions. We find the largest break in length at just above 15.5 m and in LBR at just below 5.5. Thus, we define boats longer than 15.5 m and with an LBR less than 5.5 as *sanbuqs* (Figure 4).

**Figure 4:** Estimated boat dimensions and derived boat type

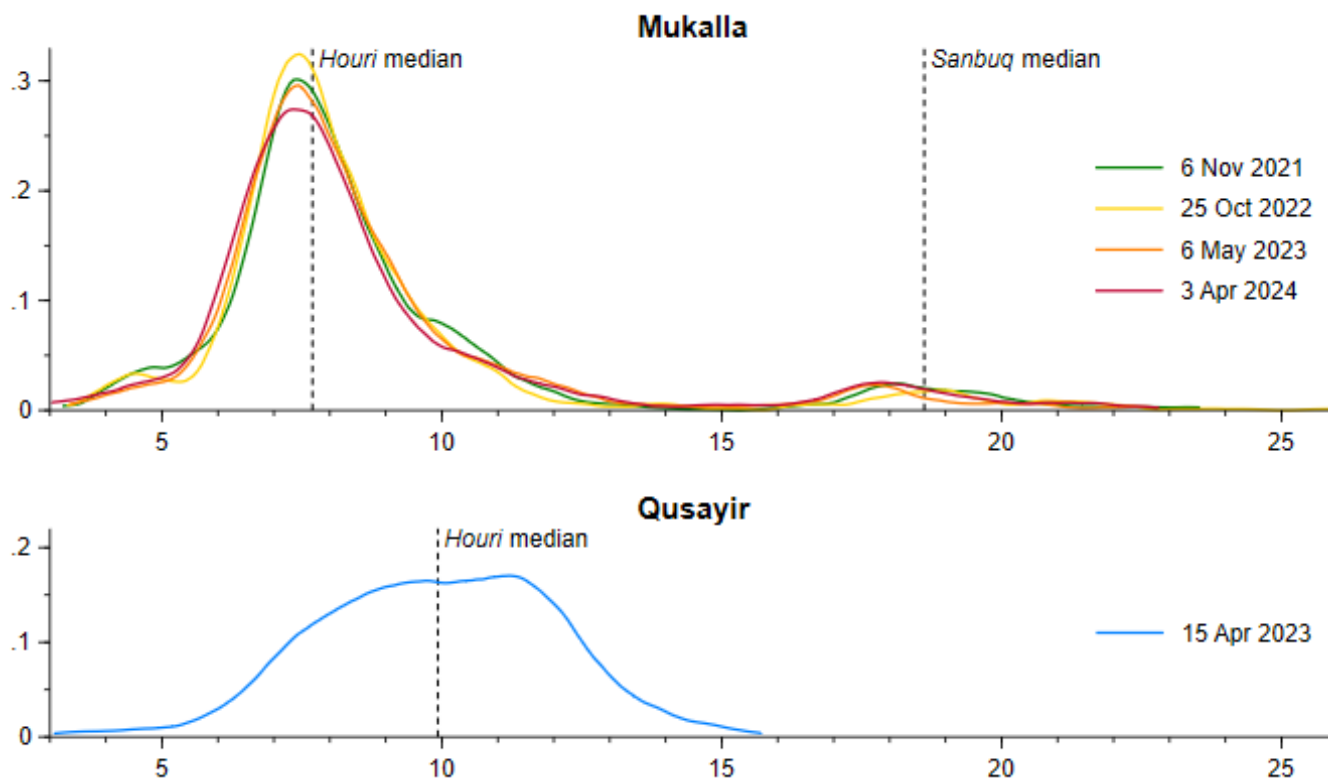


Our boat count results (Table 2) suggest that *sanbuqs* comprise about 6.9 percent of Mukalla’s artisanal fishing fleet. The year-on-year variation in the *sanbuq* count is very similar to the variation found for the total fleet. The estimated Mukalla fleet composition is consistent with the results of the landing site survey (Apex & AAMS 2025): *Sanbuqs* account for 4.0 percent of the entire artisanal fishing fleet of Hadramawt Governorate. *Sanbuqs* are likely concentrated in Hadramawt’s two major fisheries hubs, Mukalla and Ash Shihr, as they require larger-scale fisheries infrastructure to land their catch and have difficulties operating out of more common beach landing sites, such as in Qusayir. Our estimates confirm that no boat in Qusayir had dimensions that match the classification criteria for *sanbuqs*.

## Fleet composition

Unlike the found boat count, the composition of the Mukalla’s artisanal fishing fleet by boat type and length is quite stable over the four-year observation period of this study (Figure 5). Hence, we do not find evidence of systematic shifts toward larger (or smaller) boats or greater segmentation by boat length. Our results also indicate that *houris* are on average longer in Qusayir than in Mukalla, at estimated lengths of about 10 m and 8 m, respectively. The distribution of estimated boat length for the Qusayir fleet is significantly wider than that of Mukalla’s fleet. However, estimated boat length is possibly measured with less accuracy in Qusayir than Mukalla—the site used for training our deep-learning model. Nevertheless, by boat length class, the estimated composition of the Mukalla and Qusayir fleets together is similar to the composition of the entire artisanal fishing fleet of Hadramawt, as found in the landing site survey (Apex & AAMS, 2025) (Table 3).

**Figure 5:** Kernel density of estimated boat length (meters) by location and satellite image



**Table 3:** Fleet composition comparison by boat type and length class

Boat type	Length class	YOLO11 OBB model estimates			Landing site survey*
		Mukalla (ave.)	Qusayir	Mukalla & Qusayir	Hadramawt Gov.
Total	≤ 5 m	3.7%	1.1%	3.4%	15.8%
	6 – 10 m	79.4%	49.8%	75.7%	63.8%
	11 – 15 m	9.7%	48.7%	14.5%	18.4%
	16 – 20 m	5.5%	0.4%	4.9%	1.8%
	≥ 21 m	1.7%	—	1.5%	0.2%
<i>Houri</i>	≤ 5 m	4.0%	1.1%	3.6%	16.0%
	6 – 10 m	85.2%	49.8%	80.5%	64.6%
	11 – 15 m	10.4%	48.7%	15.4%	18.6%
	16 – 20 m	0.4%	0.4%	0.4%	0.8%
	≥ 21 m	—	—	—	0.1%
<i>Sanbuq</i>	11 – 15 m	—	—	—	2.4%
	16 – 20 m	75.2%	—	75.2%	84.1%
	≥ 21 m	24.8%	—	24.8%	13.5%

Note: \* Survey by Apex and AAMS (2025).

## Fishing capacity

Dimensions of fishing vessels are typically correlated with their fish hold capacity. To obtain rough estimates of the fish catch capacity of the Mukalla and Qusayir artisanal fishing fleets, we first approximate the general relationship between hold capacity and length by boat type, using estimates from the Apex and AAMS (2025) report. Specifically, we feed reported frequency statistics for hold capacity categories and boat length class into a generative AI tool to identify the parametric functional forms that yield the best model fit of the data. For *houris*, the found relationship is positive, monotonic, and nonlinear, with weak scaling at small lengths and mild convexity emerging at larger lengths. There is little variation in the length of *sanbuqs* (Table 3), and the reported hold capacity of almost all *sanbuqs* falls in the highest category of 10–30 mt regardless of boat length, suggesting a constant capacity–length relationship for the observed boat length. Next, for *houris*, we apply the best-fit function on our estimated boat length data to predict hold capacities.<sup>4</sup> For *sanbuqs*, we assign the average hold capacity of 15.2 mt to all boats of this type.

Our back-of-the-envelope estimation suggests that, in Mukalla, the fish catch capacity of the *houris* fleet varied around 1,290 mt, and the capacity of the *sanbuq* fleet around 828 mt, per fishing trip (Table 4). As fishing trips are more frequent on *houris* than *sanbuqs*, the fish catch capacity of the *houris* fleet exceeds that of the *sanbuq* fleet multiple times over. Despite fewer—but, on average, longer—*houris* boats, the estimated catch capacity of Qusayir’s *houris* fleet (1,133 mt per fishing trip, measured in April

<sup>4</sup> The mean hold capacity of *houris* in our pooled sample is about 1.8 mt, and the median is around 1.5 mt.

2023) is close to that of Mukalla’s *hour* fleet. These estimates clearly mark the upper bound of the artisanal fisheries’ production potential. Actual fish landings are presumably small fractions of the maximum capacity; however, accurate local fish catch records for comparison are unavailable. To put these estimates into perspective, Yemen’s total fisheries production is estimated to have totaled 151,026 mt in 2023, equivalent to 414 mt per day across the year (FAO, 2026), with the Gulf of Aden fisheries contributing about two-thirds of the total (Impact Consulting, 2022).

While the estimated fish catch capacities should be interpreted cautiously, this simple ballpark assessment clarifies that, overall, fishing boat sizes in the Mukalla and Qusayir artisanal fishing fleets impose no catch capacity constraints. Consistent with this finding, most fishers interviewed in the landing site survey reported that their boats’ hold capacity was sufficient (Apex & AAMS, 2025). Sufficient hold capacities can also explain the observed constancy of Mukalla’s fleet composition, as limited available fish resources and other constraints of artisanal fisheries made boat upgrades economically unreasonable during the study period (2021–2024).

**Table 4:** Estimated fish catch capacity

Location	Image date	Boat type	
		<i>Houri</i>	<i>Sanbuq</i>
Mukalla	6 Nov 2021	1,461	1,034
	25 Oct 2022	1,283	760
	6 May 2023	1,158	669
	3 Apr 2024	1,257	851
	<i>Average</i>	<i>1,290</i>	<i>828</i>
Qusayir	15 Apr 2023	1,133	–

## Conclusions

In this pilot study, we show that VHR satellite imagery-based deep-learning models can accurately detect artisanal fishing boats. Artisanal fisheries account for the largest share of total fish production in many developing countries, and the share is estimated at more than 90 percent in the case of Yemen. Artisanal fishing activities can only be measured and monitored by observation, unlike commercial fishing activities. International and national regulations require large commercial fishing boats to carry and activate transponders for ship safety, collision avoidance, and fisheries management. GIS data from fishing vessels’ transponders can be used for tracking their locations and movements, and to infer fishing activities, as done by Global Fishing Watch and similar online information and monitoring services. The remote sensing methodology proposed in this study offers a practical approach to complement the transponder-based fishing information and monitoring systems on large commercial boats with data on artisanal fisheries. Together, these two methods can provide a more complete picture of fishing activities and fish resource harvesting by both commercial and artisanal fishers.

Comprehensive landing site surveys like the one carried out recently by Apex and AAMS (2025) along Yemen’s Gulf of Aden coast are essential for clarifying the current situation of artisanal fisheries, and

for establishing a baseline for further assessment. They can also provide benchmarks for validating remote sensing approaches to measure fishing activities. Such surveys, however, provide only a snapshot of the status quo—at the time landing sites were visited—which may not be an accurate representation of fishing activities at another point in time. Surveys are impractical for examining temporal and spatial variations across a large area, like the Gulf of Aden coastline. Nevertheless, analyzing temporal and spatial variations at disaggregated levels is important for understanding fishing dynamics in response to trends and seasonal patterns of fish stock growth and migration (which can be affected by overfishing and climate change) and in response to external shocks such as conflict or high fuel prices. Our remote sensing approach can address this data and knowledge gap and provide frequent observations from many locations at similar points in time.

More broadly, satellite imagery-based deep-learning for vessel detection offers several advantages over conventional surveys. First, it is flexible in geographic extent and scale: VHR imagery is now widely available with broad (often near-global) coverage, so the same workflow can be applied to a single landing site, all landing sites along a country's coastline, or entire coastal regions of an ocean sea, without deploying field teams. Second, the methodology provides a more objective and standardized measurement approach, in that the same imagery and model rules can be applied consistently across locations and time points. Because the methods are repeatable, it enables high-frequency monitoring and automated near-real-time updates when new imagery is available. It is therefore also possible to look back in time using archived imagery to investigate historical trends and patterns, which is usually impossible with surveys. The transferability of the modeling approach also facilitates comparisons across sites and over time. Third, the methodology is inexpensive, especially relative to surveys, and is therefore applicable even in large, longitudinal studies and donor-funded projects confronted with declining budgets for research and protection of common natural resources. Fourth, it is applicable in hard-to-reach sites, such as conflict or disaster-affected areas and locations where local authorities prohibit access by field teams.

We developed and tested three deep-learning model variants using VHR satellite imagery from two study sites in Hadramawt Governorate. With an overall model accuracy of 96.9 percent, the YOLO11-OBB model performs best based on training and validation datasets from the primary study site in Mukalla—a major fisheries hub in Yemen. We apply this model also to data from our secondary study site in Qusayir—a typical node in Yemen's artisanal fisheries. The landing sites in Mukalla and Qusayir have very different features that together encompass a broad range of various object and background combinations that challenge the model's boat detection processes and are similar to those in many other landing sites along the Gulf of Aden coast. Visual inspection of the model outputs suggests high boat detection accuracy, which increases our confidence in the transferability of our remote sensing approach. The YOLO11-OBB model is also the variant that enables accurate boat length and beam measurements. By measuring boat dimensions, we go further than previous machine learning-based remote sensing studies in fisheries that focus primarily on object counts. We showcase that boat dimension measurements provide meaningful estimates of artisanal fishing fleet composition by boat type and size. In combination with survey-based estimates, these modeled results can be further used to approximate benchmark figures of fish production such as the fleet's fish catch capacity, for example.

Our modeled results suggest that, by boat count, Mukalla's fleet, with an average of 800 boats in 2021–2024, is about 1.5 times larger than Qusayir's fleet, with 450 boats in April 2023. These numbers are not consistent with estimates from the landing site survey conducted by Apex and AAMS (2025) between June 2024 and March 2025. The survey-based counts imply that Mukalla's fleet, with about 540 boats, is considerably smaller than Qusayir's fleet, with about 660 boats. While possible explanations

for different estimates include issues of survey coverage, time of data collection, and differentiation between detected operational boats and boats in use, this discrepancy requires further investigation. Notably, our modeled results on fleet composition by boat type and length class for Mukalla and Qusayir are quite consistent with the composition of Hadramawt's entire fleet found in the survey. We do not find evidence for systematic changes in the composition of the Mukalla fleet between 2021 and 2024. As this finding is based on only four data points at different times during the fishing season and only one study site, more frequent observations from different sites are needed to obtain conclusive evidence. Lastly, our back-of-the-envelope estimation of fish catch capacity highlights that the boats' hold capacities in the Mukalla artisanal fishing fleet and presumably the fleets at other landing sites impose no notable constraint to increasing productivity of Southern Yemen's artisanal fisheries.

This study presents an important first step toward a deep-learning-based remote sensing tool for monitoring and analyzing artisanal fishing activities. The found high performance of our YOLO11-OBB model and tested transfer capabilities encouraged us to take the next step. We are currently transferring the model to several different landing sites along the Gulf of Aden coast and using VHR satellite imagery series with multiple images per year over several years. Given new modeling challenges such as different light and overcast conditions and varying satellite nadir angles, additional model training and validation is required, which is also expected to further improve model accuracy. The model results will finally be used to identify spatial and temporal patterns in Southern Yemen's artisanal fisheries and to analyze policy-relevant drivers of fishing, such as fuel prices and political instability, and effects on fish consumption and food security.

---

## ABOUT THE AUTHORS

**Olivier Ecker** ([O.Ecker@cgiar.org](mailto:O.Ecker@cgiar.org)) is a Senior Research Fellow in the Foresight and Policy Modeling Unit at IFPRI.

**Zhe Guo** ([Z.Guo@cgiar.org](mailto:Z.Guo@cgiar.org)) is a Senior Geographic Information Systems Coordinator in the Foresight and Policy Modeling Unit at IFPRI.

**Hanxi Li** ([hli51@gmu.edu](mailto:hli51@gmu.edu)) is a PhD student at the Center for Spatial Information Science and Systems at George Mason University.

**Liping Di** ([ldi@gmu.edu](mailto:ldi@gmu.edu)) is the Director of the Center for Spatial Information Science and Systems and a Professor in the Department of Geography and Geoinformation Science at George Mason University.

---

## REFERENCES

Alabsi, N., and Komatsu, T. 2014. Characterization of fisheries management in Yemen: A case study of a developing country's management regime. *Marine Policy*, 50, 89-95. <https://doi.org/10.1016/j.marpol.2014.05.015>

Ali, A., Donnat, H., Fadhl, S., Mahmood, A., Srivastav, S., and White, E.P. 2024. Empowering Yemen's fisheries: A strategy for reform through public-private partnerships. Final report YEM-23120. International Growth Centre, London. <https://www.theigc.org/publications/yemen-fisheries-strategy-reform-public-private-partnerships>

Apex (Apex Consulting) and AAMS (Advance Africa Management Services). 2025. Fisheries profile for the Gulf of Aden Coast, Republic of Yemen. Unpublished report submitted to the World Bank.

- Belton, B., Abdelhadi, A., Dey, D., Jovanovic, N., Kurdi, S., and Ecker, O. 2026. The state of fisheries in Hadramawt: Insights from a scoping review. MENA Project Note 29. Washington, DC: International Food Policy Research Institute. <https://hdl.handle.net/10568/179858>
- Bochkovskiy, A., Wang, C.Y., and Liao, H. Y. 2020. YOLOv4: Optimal speed and accuracy of object detection. arXiv Preprint arXiv:2004.10934. <https://doi.org/10.48550/arXiv.2004.10934>
- Dey, D., Belton, B., Kurdi, S., and Ecker, O. 2026. Fish for food security in Yemen: Insights from the Data in Emergencies survey. MENA Project Note 28. Washington, DC: International Food Policy Research Institute. <https://hdl.handle.net/10568/179637>
- FAO (Food and Agriculture Organization of the United Nations). 2026. Fisheries and aquaculture: Global production by production source. [https://www.fao.org/fishery/statistics-query/en/global\\_production](https://www.fao.org/fishery/statistics-query/en/global_production). Accessed March 22, 2026.
- GFW (Global Fish Watch). 2020. Fisheries intelligence report GFW-TMT-NWIO-02-2020. [https://drive.google.com/file/d/1-eB3OI-9Y68JNY9\\_q6bxbCwMcYiMDsV0/view](https://drive.google.com/file/d/1-eB3OI-9Y68JNY9_q6bxbCwMcYiMDsV0/view)
- Impact Consulting. 2022. Yemen fisheries assessment report. Unpublished report submitted to UNDP.
- Kawarazuka, N., and Béné, C. 2011. The potential role of small fish species in improving micronutrient deficiencies in developing countries: Building evidence. *Public Health Nutrition*, 14(11), 1927-1938. <https://doi.org/10.1017/S1368980011000814>
- Redmon, J., Divvala, S., Girshick, R., and Farhadi, A. 2016. You Only Look Once: Unified, real-time object detection. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 779-788). <https://doi.org/10.1109/CVPR.2016.91>
- Robinson, J. P., Mills, D. J., Asiedu, G. A., Byrd, K., Mancha Cisneros, M. D. M., Cohen, P. J., ... and Hicks, C. C. 2022. Small pelagic fish supply abundant and affordable micronutrients to low- and middle-income countries. *Nature Food*, 3(12), 1075-1084. <https://doi.org/10.1038/s43016-022-00643-3>
- World Bank (2025). Sustainable fisheries for Yemen's resilience. Featured story, November 20, 2025. <https://www.worldbank.org/en/news/feature/2025/11/20/sustainable-fisheries-for-yemen-s-resilience>
- UNDP (United Nations Development Programme). 2024. Fish value chain analysis, Ash Shihr District, Hadramaut – Yemen. <https://www.undp.org/yemen/publications/fish-value-chain-study-ash-shihr-hadramout-yemen>

This work was undertaken as part of the “Strengthening Resilience and Participation at Local Level in Yemen” project. The project is funded by the Federal Ministry for Economic Cooperation and Development (BMZ) of Germany and implemented by the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH. We would like to thank BMZ and GIZ for the support, and Johannes Kurt Becker for his valuable comments to a draft version of this Project Note. We are grateful to Osan Bahurmiz for his first-hand insights and to Nina Jovanovic for her critical reading of the draft version.

## INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

*A sustainable world free of poverty, hunger, and malnutrition*

IFPRI is a CGIAR Research Center

1201 Eye Street, NW, Washington, DC 20005 USA | T. +1-202-862-5600 | F. +1-202-862-5606 | Email: [ifpri@cgiar.org](mailto:ifpri@cgiar.org) | [www.ifpri.org](http://www.ifpri.org) | [www.ifpri.info](http://www.ifpri.info)

© 2026 International Food Policy Research Institute (IFPRI). This publication is licensed for use under a Creative Commons Attribution 4.0 International License (CC BY 4.0). To view this license, visit <https://creativecommons.org/licenses/by/4.0>.