Developing a Fishing Risk Framework from Satellites and Ocean Data

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Abstract

The lack of traceability within the fishing industry limits responsible governance, and management of the oceans. As a consequence of this lack of traceability illegal, unregulated and unreported fishing is rife, affecting fisheries worldwide. A major challenge within fish traceability is determining whether fish have been caught sustainably from vessels acting in a legal, and responsible manner. The proof-of-concept system proposed here creates a vessel risk framework to assess the likelihood that a vessel has engaged in illegal, unregulated, or unreported fishing.

Using historical vessel tracking data the system first predicts the likelihood at each time point that a vessel was fishing, using features including its movement and distance from shore. Vessels that are fishing are then scored using multiple indicators to evaluate the risk of these behaviours. Indicators include the likelihood that a vessel has previously fished in a marine protected area or exclusive economic zone, and the intermittency of the vessels automatic identification system positional signal. This information is displayed in web application that allows the user to weight the components according to the use case, or for convenience combined into a unified vessel risk score.

This proposed fishing risk framework combines multiple data sets by correlating these tracking data with satellite imagery. For all historical vessel tracking and all time points the available satellite imagery is found, this could be used as further evidence to substantiate our risk indicator. This proof-of-concept shows show how multiple data sources can be combined to start building a library of historic evidence and data of a vessels behaviour. This gives governments, retailers, coastguards and enforcement agencies the information they need to improve traceability within the fishing industry, better manage the oceans, and conduct more effective enforcement.

Contents

1 Introduction

Ocean fisheries provide a vital source of food, employment, recreation, trade, and economic security for people throughout the world. Over three billion people depend on marine and coastal resources for their livelihoods, with a global market value of $3 trillion per year or about 5% of global GDP. Oceans serve as the world's largest source of protein, with more than 3 billion people depending on the oceans as their primary source of protein [1]. These resources need to be properly managed if their contribution to the nutritional, economic, and social well-being of the world's growing population is to be sustained.

1.1 Illegal, unreported, and unregulated fishing

Since the advent of industrialised fishing practices in the 1950s fish stocks have been in decline. Large predator species such as tuna are estimated to have declined by 90% [2]. Their depletion not only threatens the future of these fish, but the livelihood of the fishers that depend on them, and the equilibirum of the ocean ecosystem. The proximate causes of overfishing are: limited or ineffective harvest regulations, overcapacity of fishing fleets, destructive fishing practices, and IUU fishing. The ultimate causes of overfishing are institutional constraints, and a limited capacity to manage fisheries, including limited information and ability to control illegal activities.

Estimating the extent of the IUU fishing problem is difficult, since by nature these fishing practices are illicit and concealed. The IUU catch is in addition to a world annual catch of fish and other marine fauna of approximately 80 million tonnes. This IUU fishing problem is particularly problematic because it can lead to overfishing for a given maritime region. According to the Food and Agriculture Organisation (FAO) Fisheries and Aquaculture Department, illegal fishing causes losses estimated at $23 billion per year with about 30 percent of illegal fishing in the world occurring in Indonesia.

The driving force behind IUU fishing are similar to those behind many other types of international environmental crime: pirate fishers have a strong economic incentive. Many species of fish, particularly those that have been overexploited and are thus in short supply, are of high financial value. These IUU fishing practices are systemic in many fisheries worldwide, and are generally linked to weak governance. IUU fishing is a key challenge to overcome in order to achieve sustainably managed fisheries.

1.2 Sustainable Development Goals

The United Nations (UN) coordinates international collaboration in addressing global challenges in environmental protection, whilst fostering social and economic development. The UN and it's member states devised a set of 17 Sustainable Development Goals (SDGs) covering a broad range of sustainable development issues. Goal number 14 Life Below Water is concerned with the conservation and sustainable use of the oceans, seas and marine resources. By 2020 this goal sets out to:

- effectively regulate fisheries harvesting,
- implement science-based management plans, and,
- end overfishing, illegal unreported and unregulated (IUU) fishing.

If these goals are met then fish stocks can be maintained at the level capable of producing the maximum sustainable long-term yield.

1.3 Objective

In collaboration with the World Economic Forum (WEF) this project set out to create a tool to use data, and data science approaches, to guide and enhance fisheries power to enforce and control IUU fishing. The premise of which was to create a vessel fishing risk index based on a series of quantitative metrics to indicate vessels that are likely to engage in IUU fishing. A proof-of-concept open source tool was developed using aggregate data sets from sources such as satellite imagery, synthetic-aperture radar (SAR), and automatic identification system (AIS) data. The tool provides indicators of vessels fishing illegally, allowing for more targeted enforcement whilst encouraging responsible fishing practices.

2 Ocean data

An effective approach to combatting IUU fishing will be multifaceted and require multiple. This approach will most likely have to target the underlying causes of IUU fishing, improve traceability within the supply chain, and improve detection and enforcement of IUU fishing. Monitoring fishing activity at sea is especially challenging in the high seas.

Technological advancements are providing improved transparency, and traceability in the fish supply chain such as using distributed ledger blockchain technologies. Satellites are also being used to collect ever increasing amounts of vessel tracking data, oceanographic data, and imagery. We are also witnessing the beginnings of autonomous drone usage for monitoring and enforcement of IUU fishing.

2.1 Automatic identification system

The most comprehensive existing vessel location and tracking service is provided by automatic identification system (AIS). This is an automated, autonomous tracking system, extensively used in the maritime world for the exchange of navigational informational between AIS-equipped terminals. The system was devised for the purposes of collision avoidance and navigation. Transponders installed on vessels broadcast messages that can be received by nearby vessels as well as low-earth orbiting satellites, or land based stations if close to land.

A vessel's onboard AIS system consists of one very high frequency (VHF) transmitter, two VHF receivers, and one VHF digital selective calling module to receive distress signals. This information is displayed on a standard marine electronic communications link to shipboard display and sensor systems. Positional information is derived from an inbuilt global positioning system (GPS) receiver or an external one.

These transponders broadcast two types of messages. First, they transmit positional signals every $\approx$ 10 seconds, reporting GPS coordinates and navigational features of the vessel (i.e., speed, course, and heading). The second type of message is static and is reported every $\approx$ 30 seconds, these features include ship name, callsign, length, and port destination.

Beacons near the shores capture these messages, working as an avoiding collision system with the sea coast and other vessels. This makes AIS an important component of maritime security [13]. Coastal receivers do not always capture AIS signals away from shore, with a maximum range of approximately 80 kilometers range. Low-orbit satellite captured AIS signals collect vessel information further out at sea. This allows us to retrieve vessel tracking data from all over the world, and not only from vessels near seashores.

There are some caveats to using AIS data. First, AIS signals fetched by satellites can *bunch together* leading to data loss, since the receiver is only able to process a limited number of signals at a time. Second, the positional accuracy of the signal is not always certain. Hence there is a possible measurement error in the location and other features of the vessel. Lastly, there is the possibility of tampering with the AIS transponder to for example spoof the vessels involved in illegal activities. The most significant downside of AIS is that vessels may simply turn off their transponder in order to engage in IUU activities.

2.2 Satellite imagery

To visually validate the AIS data, we used different sources of proprietary satellite imagery for the same timeframe of the positional AIS data. We rely on two sources of high-definition satellite imagery. The first source is Digital Globe (henceforth GBDX) which reports images with visual and Near Infrared (NIR) bands with a resolution of $\approx$ 3 meters per pixel. Second, we used imagery from Planet Labs, which has higher revisit times that GBDX, but at the cost of lower resolution (from $\approx$ 10 m. to $\approx$ 3 m. over the equator).

Images from both sources were orthorectified and projected into a common grid. The first process corrects possible terrain distortions due to higher elevation angles [1] The second process projects the images into a common grid to georeference them into a common grid, usually under a *UTM* local projection. Despite the availability of more advanced image processing tasks, as *Pansharpening* or *Atmospheric compensation*, we decided to use a single approach. Also, some advanced image processing tasks merge visual and NIR bands, hindering the use of a multispectral or thermal analysis.

[1] This angle is commonly known as Nadir. The terrain displacement occurs when satellite sensors are not orthogonal to the earth terrain. Thus the optimal Nadir angle is 90°.

2.3 Synthetic-aperture radar

3 Related projects

The first step in investigating a myriad of vessel activities including piracy, illegal maritime traffic, and IUU fishing is to find where the ships are. In the literature approaches for ship detection are described using multiple algorithms and applied to various geospatial data sources. For example using satellite-based SAR and a discrete wavelet transform to capture spectral signals of vessels in the ocean [3]. The use of SAR data for this task is common in the literature [4–7], this has the advantage of being weather independent[2]. The ability of the SAR sensors to capture signals even in the presence of high cloud coverage gives radar data an advantage over visible (optical) data. Nonetheless, vessel detection with SAR data has limitations for identifying small ships, limited coverage, and its automatic interpretation can be a cumbersome process [8].

[9], shows a first apporach to vessel detection using panchromatic high-resolution imagery from the SPOT-5 program. The authors used a wavelet transform, which decomposes the image according to light frecquency profiles and used a novel preprocessing approach that allows having rapid classifications compared with other algorithms. [10] also uses optical data to track vessels, although the authors use the NASA-VIIRS nightlight data. The results of the classification algortihm are cross-validated using vessel positional AIS data, confirming the correct indetification of 5000-6000 ships per night, but is not clear if this approach is suitable to identify small targets, like fishing vessels.[3].

Image classification is not the only approach to track vessels on the ocean. Positional messages are also used to classify ship activity. The project Global Fishing Watch for example used a labelled set of fishing vessels to classify vessels in automatic identification system (AIS) data as fishing or non-fishing, this is described in [12]. This approach relies on a reliable AIS signal, and vessels fishing illegally may not have a transponder, may switch it off, or may spoof its signal to engage in these behaviours. As such this should not be relied upon as the only approach to identify vessels. Here we have used a similar model to identify fishing vessels, but plan to incorporoate other vessel detection methods.

4 Detecting whether a vessel is fishing at a given point

One of our primary objectives is to identify vessels that are fishing in maritime protected areas.

International Union for Conservation of Nature - IUCN has defined MPAs as follows: 'A clearly defined geographical space, recognised, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values'.

MPAs are classified into several categories based on the fishing restrictions. Restrictions may vary from protecting particular species to no fishing allowed.

Being able to identify weather a vessel is fishing at any point along its trajectory will help us identify vessels fishing in MPAs and Exclusive Economic Zones.

5 Data

We are using the AIS data provided by Spire. AIS transceivers send positional data every 2-10 seconds and static data every 6 minutes.

The positional AIS data contains the following fields:

- The vessel's Maritime Mobile Service Identity (MMSI) : a unique nine digit identification number.
- Navigation status : "at anchor", "under way using engine(s)", "not under command", etc.
- Rate of turn : right or left, from 0 to 720 degrees per minute
- Speed over ground : 0.1-knot (0.19 km/h) resolution from 0 to 102 knots (189 km/h)

[2]Most of these documents rely on the *TerraSAT* project data which have a resolution up to ≈ 16 meters.

[3]VIIRS day-night band, as its predecesor, the NOAA-OLS, has a lower resolution (1 km^2 at the equator), and other problems like overglooming in the coastlines that can yield false positives. To read a comprehensive assessment of the use of nightlight data to data analysis see [11]

- Positional accuracy: Longitude : to 0.0001 minutes Latitude : to 0.0001 minutes
- Course over ground : relative to true north to 0.1Âř
- True heading : 0 to 359 degrees (for example from a gyro compass)
- True bearing at own position. 0 to 359 degrees UTC Seconds : The seconds field of the UTC time when these data were generated.

The static data contains the following fields:

- IMO ship identification number : a seven digit number that remains unchanged upon transfer of the ship's registration to another country
- Radio call sign : international radio call sign, up to seven characters, assigned to the vessel by its country of registry
- Name : 20 characters to represent the name of the vessel
- Type of ship/cargo
- Dimensions of ship : to nearest meter
- Location of positioning system's (e.g., GPS) antenna on board the vessel : in meters aft of bow and meters port or starboard
- Type of positioning system : such as GPS, DGPS or LORAN-C.
- Draught of ship : 0.1 meter to 25.5 meters
- Destination : max. 20 characters
- ETA (estimated time of arrival) at destination : UTC month/date hour:minute

We have access to an year of worldwide AIS messages. We also used the training data provided by Global Fishing Watch. The data contains positional data and the labels for weather the vessel was fishing at that point or not. This data set was labeled for 90 vessels over a period of 3 years.

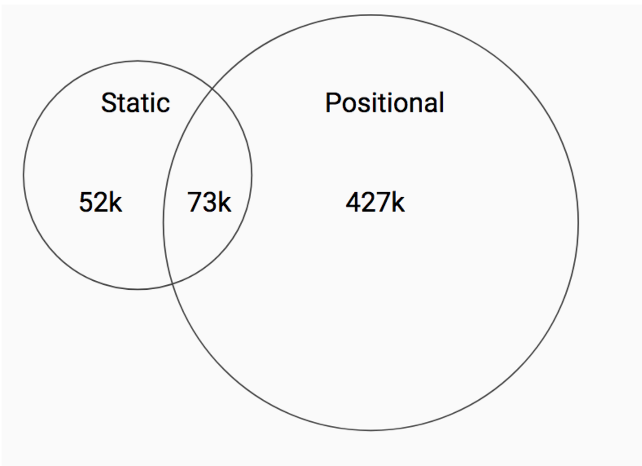


Figure 1: Number of positional and static AIS messages for a period of 1 year

6 Modelling

Here we describe an approach to use AIS data to identify at what points along their trajectory the vessels were fishing.

6.1 Feature generation

After discussions with domain experts, we came up with a list of features that might be good indicators of fishing behavior. We generated features like distance from shore, port, day or night during the time of navigation etc. We then fit a Random Forest model to compute how each of the feature contributes towards the prediction.

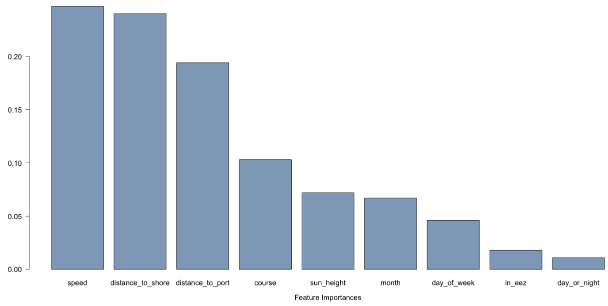


Figure 2: Feature importance for AIS positional features.

6.2 Training and cross-validation

Given we have a time series data, we split our data set into multiple temporal folds. For each fold, we split the train-test set as illustrated in the following figure.

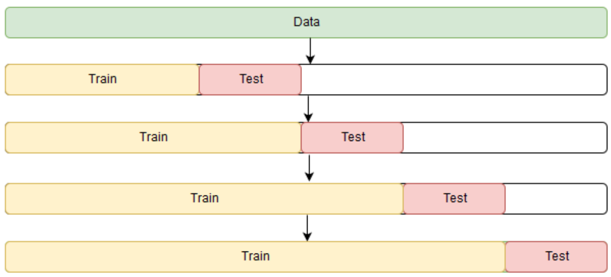


Figure 3: Temporal splits for each fold

We compute various metrics like precision, recall, false positive and true positives rates etc.

6.3 Model selection

After talking to our partners, we came to the conclusion that we want to optimize for precision of our models. For example, in the following figure, you can see three precision-recall curves. For the model represented by the blue curve, you see high precision at first and then the precision get worse than the same for other models. The models we select also depend on how many cases our partner can act upon. If the partner can act upon K cases, then we should select the model that maximizes precision for those K cases.

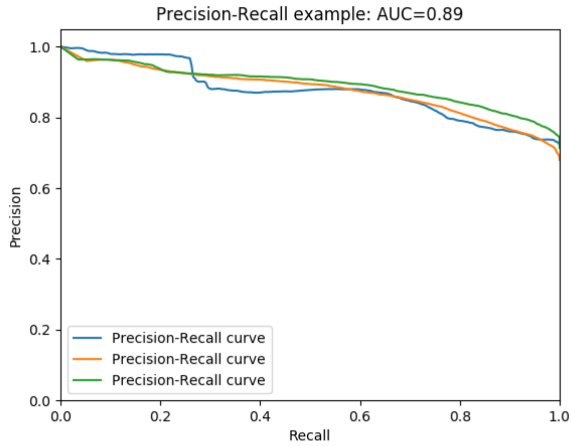


Figure 4: Precision-Recall curve for different models

7 Evaluation

In the absence of a labeled prediction set, we are employing a few heuristics to examine the performance of our models. For example, average fishing score for reported fishing vessels should in general, be greater than the same for vessels that don't report themselves as fishing.

Vessels spend most of their time being docked. Also, reported fishing vessels spend only a small fraction of their time actually fishing.

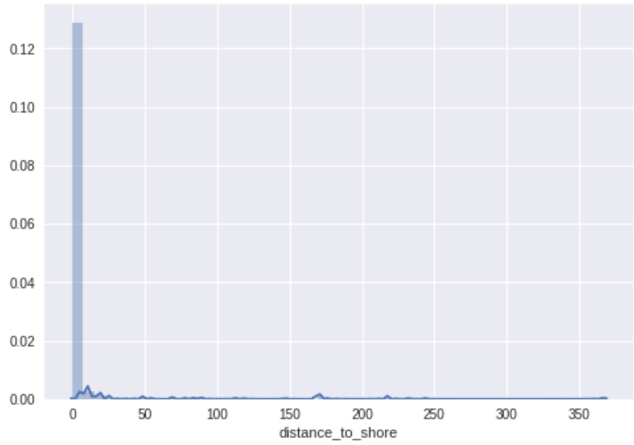


Figure 5: Distribution of distance to shore in the AIS messages

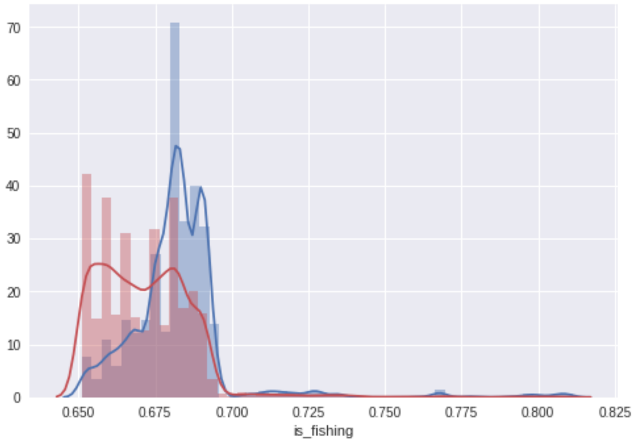


Figure 6: Fishing score distributions for reported and non reported fishing vessels.

7.1 Intersection AIS and Satellite imagery

Marine traffic detection using remote sensing approach is a commonly addressed task. [5] showed how AIS and Synthetic Aperture Radar (SAR) data could be used in conjunction to detect vessels in small portions where the satellite imagery tiles contain positional AIS messages. [6] follow a similar approach joining Vessel Monitoring System (VMS) and commercial satellite imagery to identify common features of shrimp boats. Although these endeavors are working solutions, there is still wanting a strategy that can bring different sources of data that can complement SAR data. One of these possible sources of data is high-resolution imagery, which until now has been restricted to commercial use only [14].

Our approach follows the work previously outlined since it is combining positional GPS data with remote sensing data. Nonetheless, it departs from it since it is mainly focused on UII activities, and also uses worldwide satellite imagery and AIS positional data. This work, at least in this preliminary stage, can work to create a comprehensive image database that can serve ultimately to validate the AIS data accuracy, and also the feasibility of joining different data sources to understand risky behaviors related to UII.

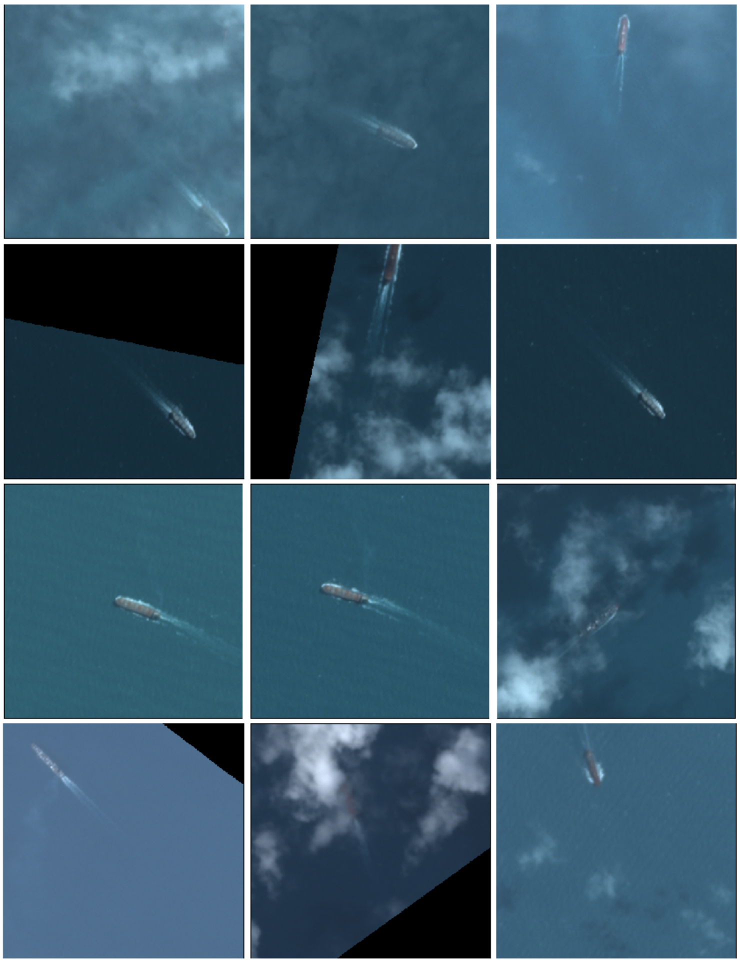
The process of image retrieval was a tree step operation. First, we retrieve all the available images in *Marine Areas* and *Ocean Areas* for our time frame (May 2016 to June 2017). The former are defined as areas is open waters; meanwhile the latter are the areas near the continental land. This process yielded 187.038 images.[4]. Second, we overlap the bounding boxes of the imagery tiles with the AIS positional signals. This process was not only a spatial join, but also a time join which took into account the difference of time between the picture capture timestamp and the positional AIS timestamp. Figure 7 shows the outcome of this step. In total, for Digital Globe, the intersection retrieved 1.072 AIS positional signals (487 unique vessels). Third, we crop the images using a 800 meters square buffer of each the AIS coordinates inside the overlap. The Figure 8 shows the final outcome of this process.

[4]Additional 18.476 images were retrieved using Planet imagery only for the Torres Strait.

Figure 7: Overlap Digital Globe and AIS data (May 2016 - June 2017)

Source: Digital Globe, Spire and OpenStreetMap.

Figure 8: Cropped images from Planet (May 2016 - June 2017)



Source: Planet and Spire.

8 Evaluation methodology

evaluate this

9 Future work

The *Oceanai* foundation broadly aims to develop nascent technologies and validate use cases, to demonstrate the efficacy of technologically guided solutions in accordance with SDG 14.

Acknowledgement

The authors would like to thank x, y, and z for their dedication.

Glossary

AIS or automatic identification system (AIS) is an automatic tracking system used on vessels, and monitored by vessel tracking services. Satellites can be used to detect AIS signatures, the term Satellite-AIS (S-AIS) is used. AIS is primarily used for collision avoidance. Typical data includes vessel name, details, location, speed and heading. Global AIS transceiver data collected from both satellite and internet-connected shore-based stations are aggregated and made available on the internet through a number of service providers. Data aggregated in this way can be viewed on any internet-capable device to provide near global, real-time position data from anywhere in the world. Typical data includes vessel name, details, location, speed and heading on a map, is searchable, has potentially unlimited, global range and the history is archived. Shore-based AIS receivers contributing to the internet are mostly run by a large number of volunteers.. 3, 4

FAO or the Food and Agriculture Organization of the United Nations (FAO) is a specialised agency of the United Nations that leads international efforts to defeat hunger. Serving both developed and developing countries, FAO acts as a neutral forum where all nations meet as equals to negotiate agreements and debate policy. FAO is also a source of knowledge and information, and helps developing countries in transition modernize and improve agriculture, forestry and fisheries practices, ensuring good nutrition and food security for all.. 3

Illegal fishing takes place when vessels or harvesters operate in violation of the laws and regulation of a fishery. This may be for example disregarding fishing times, or fishing in protected areas. This can apply to fisheries that are under the jurisdiction of a coastal state or to high seas fisheries regulated by regional fisheries management organisations.. 3

IUU illegal, unreported, and unregulated fishing. 3–5

SAR or synthetic-aperture radar is a form of radar that is used to create two- or three-dimensional images of objects, such as landscapes. SAR uses the motion of the radar antenna over a target region to provide finer spatial resolution than conventional beam-scanning radars. SAR is typically mounted on a moving platform, such as an aircraft or spacecraft.. 3, 5

SDG the sustainable development goals (SDGs) are a set of 17 "Global Goals" with 169 targets. These goals and targets cover a broad range of sustainable development issues. Examples are: ending poverty and hunger, improving health and education, making cities more sustainable, combating climate change, and protecting oceans and forests. The goals are contained in Paragraph 54 United Nations Resolution A/RES/70/1 of 25 September 2015. Their development was spearheaded by the United Nations through a process involving its 193 Member States, as well as global civil society.. 3, 11

UN the United Nations (UN) is an intergovernmental organization tasked to promote international co-operation and to create and maintain international order.. 3

Unregulated fishing are fishing activities in areas where there are no applicable management measures to regulate the catch; this is the case in the South Atlantic, for example. The term also applies to fishing for highly migratory species and certain species of shark, which is not regulated by a RFMO. And finally, the term applies to fishing activities in international waters in violation of regulations established by the relevant RFMO. Although unregulated fishing is not in fact illegal under the law of nations applicable to the high seas, it is nonetheless problematical. It results in additional fish being caught over and above the maximum catches agreed by RFMO member states for their respective regions. As a result, fully exploited stocks can easily become over-exploited.. 3

Unreported fishing are fishing activities which have not been reported, or have been misreported, by the vessels to the relevant national authority. For example this could manifest as a vessel exceeding its fishing quota.. 3

WEF the World Economic Forum (WEF) is a Swiss nonprofit foundation, recognised as an international body. The mission of WEF is cited as "committed to improving the state of the world by engaging business, political, academic, and other leaders of society to shape global, regional, and industry agendas". At the end of January the forum holds an annual meeting in the Swiss moutain resort of Davos. The meeting brings together some 2,500 top business leaders, international political leaders, economists, and journalists for up to four days to discuss the most pressing issues facing the world. The organization also convenes some six to eight regional meetings each year in locations across Africa, East Asia, and Latin America, and holds two further annual meetings in China and the United Arab Emirates. Beside meetings, the foundation produces a series of research reports and engages its members in sector-specific initiatives.. 3

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