Seychelles VMS/logbook comparison for tuna fisheries (FAO Area 51)

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SUMMARY AND CONCLUSIONS OF SEYCHELLES CASE STUDY

Seychelles high seas tuna fleets have a high AIS use with a transmission frequency considerably higher than that of VMS. However, AIS has far fewer transmissions than VMS and many more gaps in transmission longer than a few hours. The spatial coverage of the AIS data is good for Seychelles longline vessels, with acceptable coverage over the core fishing grounds. By contrast, AIS data are deficient for purse seiners and supply vessels with most data only present around ports due to the switch-off behavior linked to the piracy threat.

Consistent with data coverage, AIS seems to be very useful in describing the spatiotemporal patterns of the longline fishery and for identifying fishing hotspots. The GFW neural net algorithm predicts well the fishing operations for longliners but predictions for purse seiners are not informative. Metrics for effort at the scale of 5° x 5° squares, such as those typically used by tuna regional fisheries management organizations (RFMOs) for longline fisheries, are well correlated between logbooks and GFW algorithms. Thus, GFW is able to accurately distinguish fishing from non-fishing activities for longliners. However, the frequent breaks in transmission, perhaps due to issues with AIS reception, lead to consistent underprediction by AIS and GFW algorithms of the "true" patterns shown using VMS and logbook data. The increased satellite coverage observed between 2016 and 2017 resulted in improved GFW algorithm performance in deriving estimations of longline fishing effort.

The relationships between GFW predictions of longline fishing and effort could be useful in data-poor fisheries where poor collection and management systems may prevent the reporting of spatial effort to the RFMO. In such cases, the availability of AIS or VMS data combined with information on the number of hooks deployed per operation may enable predictions of gridded effort, which would improve compliance with the Conservation and Management Measures.

A major issue with the use of AIS data for fisheries monitoring of the Indian Ocean purse seine fleet is the low spatial coverage and switch-off behavior linked to the piracy threat. Compared to longliners, purse seiners can conduct several fishing sets per day. Thus, to achieve good predictions of purse seine fishing sets, high data coverage would be required to identify successive same-day operations from AIS data. Meanwhile, the accurate estimation of purse seine nominal effort would mainly depend on the ability of algorithms to identify non-fishing operations dedicated to the search of tuna schools. However, estimations of purse seine effort based on fishing and searching time have been complicated by the extensive use of GPS-tracked Fish Aggregating Devices. Vessel movements, which are now a combination of search and cruise, are extremely difficult to separate with the current resolution of VMS data. The high resolution of AIS data may provide a way forward.

INTRODUCTION TO THE SEYCHELLES CASE STUDY

Significant advances in monitoring fishing activity have been greatly aided by technological advances in vessel monitoring. Historically, fishing activities have been mainly monitored through fishers' logbooks and observer programs, which record daily instances of positions and quantities of catch and effort, as well as port sampling programs. Since 2006, the vessel monitoring system (VMS) was broadly adopted to complement calculations of fishing activity, increasing the temporal resolution of fisheries data from days to hours, and enabling global spatial coverage via surface-to-satellite communication (Witt and Godley 2007). Increased spatiotemporal resolution allowed calculations of effort using vessel speed profiles and bearing to identify the different vessel activities at sea (e.g., Lee *et al.* 2010; Bez *et al.* 2011). With the advent of the automatic identification system (AIS), initially implemented for ship-to-ship collision avoidance (see introductory sections), the temporal resolution of monitoring has been further refined from hours to minutes or seconds (Robards *et al.* 2016). These data are publicly accessible via satellite companies (Kroodsma *et al.* 2018), whereas access to VMS data are highly restricted and only available at the national level. This high-frequency data source has allowed the development of high precision algorithms of vessel behavior, such as those developed by Global Fishing Watch (GFW; Kroodsma *et al.* 2018) and previous work (Eguíluz *et al.*, 2016). These algorithms have the potential to identify global trends in fishing activity, and the potential to infer fisheries effort (Miller *et al.* 2018; Sala *et al.* 2018).

Seychelles high seas tuna fishery operating within and outside Seychelles EEZ is composed of two distinct components that target different markets. First, the foreign-owned industrial longline fleet is composed of 50 large ultra-low temperature freezer vessels that mainly target adult bigeye tuna (*Thunnus obesus*) and yellowfin tuna (*Thunnus albacares*) in the western and central Indian Ocean for the Japanese sashimi market and annually catch about 8 000 t of tuna. Second, a fleet of 13 foreign-owned large-scale purse seiners targets adult yellowfin in free-swimming schools and schools of skipjack (*Katsuwonus pelamis*) mixed with juveniles of yellowfin and bigeye associated with floating objects for the canning market. The total annual catch of Seychelles purse seine fleet was greater than 110 000 t during 2016-2017. It is noteworthy that Seychelles purse seine fleet also includes some non-fishing supply vessels that substantially contribute to the effort by searching for tuna schools and maintaining the network of fish aggregating devices (FADs) with satellite-tracked buoys used for increasing purse seiners' catchability (Assan *et al.* 2015). FADs are typically human-made rafts equipped with floats to ensure buoyancy and a sea sea anchor built from old fishing net that are deployed to attract schooling fish species underneath, thus increasing their catchability (Fonteneau *et al.* 2013).

Seychelles authorities are interested in investigating the potential of AIS for monitoring vessels, detecting fishing activities, and calculating fishing activity. Seychelles is a regional leader in the sustainable exploitation of marine ecosystems in the Western Indian Ocean. Seychelles government is currently developing a Marine Spatial Plan (MSP) that will protect 30 percent of its exclusive economic zone (EEZ) from fishing and extraction activities by 2021 (Figure Sey. 1). In addition, Seychelles is involved in the joint management with Mauritius of adjacent regions. In order to implement effective management plans, monitoring and compliance measures need also to be effective. Since the early 2000s, VMS in Seychelles has been well maintained and closely monitored for vessels >12 m length, but there are numerous smaller vessels that are not monitored. The high resolution of AIS data could be of interest for monitoring small-scale displacements of fishing vessels within MSP areas. In addition, AIS data may be useful when VMS data are not available due to confidentiality; for example, the VMS data of non-Seychellois vessels operating in the joint management area.

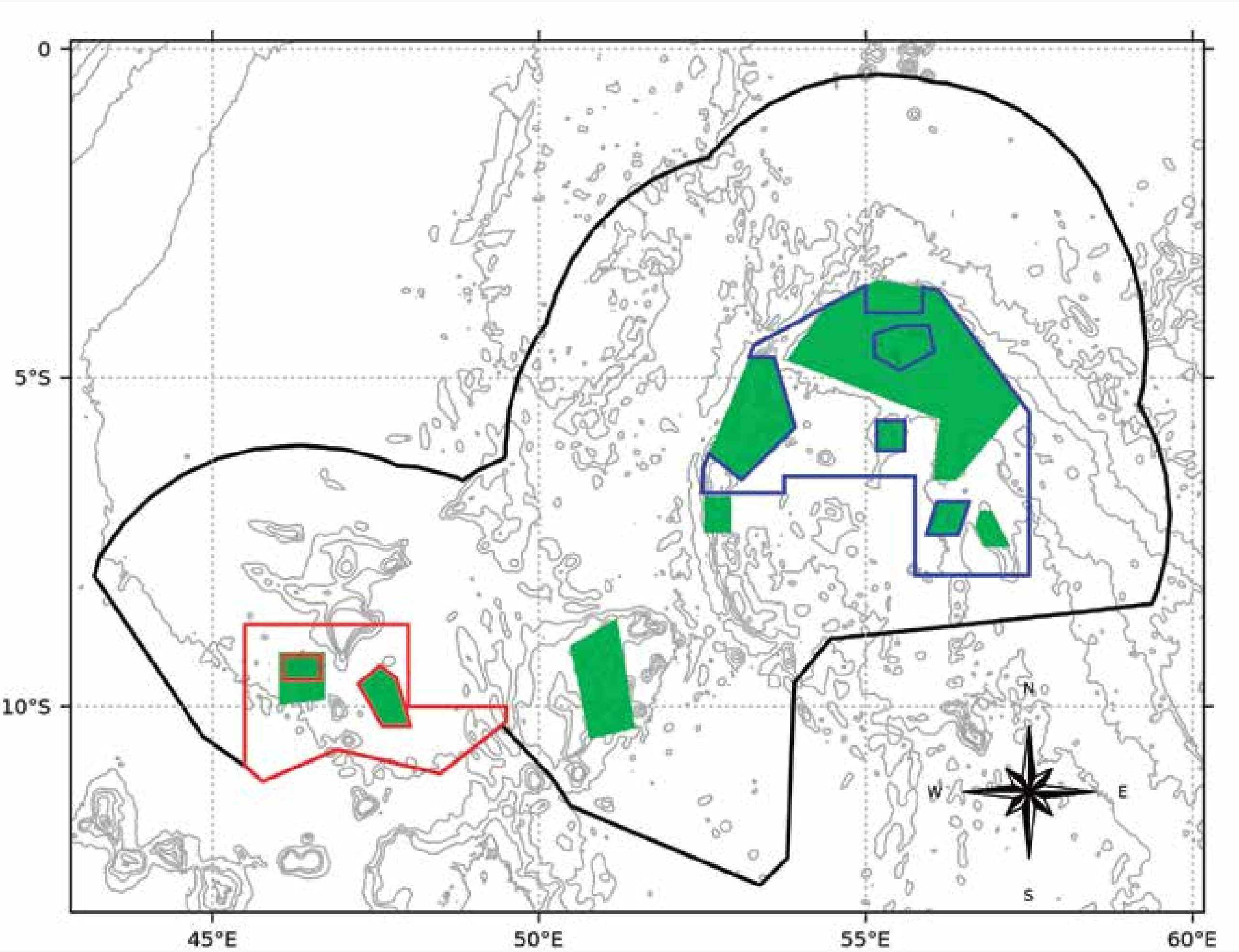

Figure Sey. 1. The exclusive economic zone (EEZ) of Seychelles (black line), located in the Western Indian Ocean, with the marine protected areas identified as part of the Fisheries Act (green polygons) and ongoing Seychelles Marine Spatial Plan as gazetted in February 2018. Red solid line = High Biodiversity Protection area; Blue solid line = Medium Biodiversity Protection and Sustainability Uses area.

Here, we investigate the difference between estimating fishing vessel activity with AIS data using GFW's algorithms and estimating fishing activity with VMS and logbook data for Seychelles high seas tuna fishery. VMS in Seychelles is continuously and rigorously monitored by Seychelles Fishing Authority (SFA), making it a highly reliable source of information on industrial fishing vessel activity. On the contrary, there are no specific mandates or requirements for AIS use in Seychelles fishing fleets. The majority of vessels that use AIS have been equipped for safety according to IMO legislation. In a first step, we compare the spatiotemporal patterns of AIS data to VMS data (i.e., the reference dataset) to investigate how well AIS data cover Seychelles industrial tuna fishing fleets and how well these data represent the spatiotemporal patterns of vessel activity. In a second step, for cases where we are able to establish that AIS data represent the spatiotemporal patterns of the fishery well, we derive indices of gear-specific fishing effort using AIS data. Finally, GFW predictions of fishing events are assessed against fishing effort and operations collected from fishers' logbooks, to assess the potential of AIS-based measures of fishing effort. We are particularly interested in assessing whether AIS could be useful for monitoring and management by the Indian Ocean Tuna Commission (IOTC) by deriving spatially aggregated effort for data-limited fisheries whose flag-countries have submitted little or no data about catch or effort.

DATA FOR THE SEYCHELLES CASE STUDY

Fishing fleets

Seychelles purse seine fleet is made up of 13 foreign-owned vessels (~90 m long) and 7 supply vessels (~40 m) that operate in Seychelles waters under annual licensing agreements. The majority of fishing by these vessels takes place on the high seas of the western tropical Indian Ocean, with ~15 percent of fishing occurring in Seychelles EEZ (Figure Sey. 1). Purse seines generally deploy their sets in waters >200 m (i.e. off the continental shelf) and can target schools between 50 m to 150 m depth.

Seychelles high seas longline fleet is made up of about 50 vessels (~50 m long), owned by locally operated Taiwanese companies that access Seychelles waters via fishing agreements. This fleet targets yellowfin and bigeye tuna in the western equatorial region with about 35 percent of fishing occurring in Seychelles EEZ. To a lesser extent, this fleet also targets albacore tuna (*Thunnus alalunga*), swordfish (*Xiphias gladius*), and oilfish (*Ruvettus pretiosus*) in the southwestern Indian Ocean near South Africa.

Data sources

Vessel activity based on AIS data for 2016 and 2017 were provided by GFW via Orbcomm (2016 and 2017) and Spire and Orbcomm (2017 only). Data were extracted specifically for drifting longliners, purse seiners, and supply vessels of Seychelles industrial tuna fishery, identified via their maritime mobile service identities (MMSI). AIS data were available for 43 longline vessels; 10 purse seine vessels; and six supply vessels (Table Sey. I). AIS data provided by GFW include information on the position of each vessel, the timestamp of this position with precision in seconds, and an indication of fishing activity based on the neural net algorithm (Kroodsma *et al.* 2018). This neural network model classifies each position as fishing or non-fishing and gives neural net scores as either 0 (no fishing) or 1 (fishing), and indicates when active fishing is occurring (i.e., a fishing operation). It does not consider effort spent searching.

VMS data for 2016 and 2017 for the longline and purse seine fleets were provided by the SFA. Data include position information of each vessel and timestamps with precision in seconds. Transmissions are required by law and frequency of emission is defined as part of the agreement protocols. Individual MMSI were associated with 47 out of the 52 distinct VMS-monitored longline vessels in Seychelles fleet, 12 out of 13 purse seiners, and seven out of seven supply vessels (Table Sey. I). The seven MMSIs missing for the VMS-monitored vessels of Seychelles fleet are due to identification errors, and the age of the vessels (i.e., very old vessels were never assigned an MMSI). Vessels with VMS and an MMSI can then be matched to vessels with AIS via the MMSI.

Logbook data were provided by the SFA and include information on the location, date, and catch for longline and purse seine vessels in 2016 and 2017. For both gears, we checked the VMS data against the date and location of each fishing set reported in the logbooks. Logbooks also provide information on the effort of each set, measured as 1) the number of hooks deployed for each fishing set for longliners, and 2) the hours at sea for purse seiners during daylight as these vessels do not operate at night. These logbook data constitute the basis of the aggregated catch-effort data reported by SFA to IOTC and were assumed to be comprehensive and accurate.

Preprocessing of the data

For the subsequent analyses, only the VMS and logbook data with a matching MMSI to AIS data were used (Table Sey. I, Figure Sey. 2). Data were further processed to remove impossible positions (i.e., on land or not on the globe); speeds > 13.5 knots for drifting longliners, > 18 knots for purse seiners and > 15 knots for supply vessels; distances < 5 m between each transmission; and points transmitted from within 10 km around ports. Finally, as VMS and AIS transmissions can be received by more than one satellite, data were filtered for positions that had duplicate timestamps. These duplicated timestamps gave positions that were generally < 500 m from each other, and we retained the mean of the two (or more) positions. Altogether, the filtering process for VMS data removed about 37 percent of longline data, 45 percent of purse seine data, and 37 percent of supply vessel data. For AIS data, about 39 percent of longline data, 88 percent of purse seine data, and 82 percent of supply vessel data were removed. The majority of the AIS data filtered from purse seine and supply vessel data were within 10 km around ports. Logbook data that did not have corresponding AIS data represented 34 percent of longline records and 27 percent of purse seine records. These missing data may be due to vessels not using AIS, issues with AIS reception, or potential misclassifications by GFW of fishing activity.

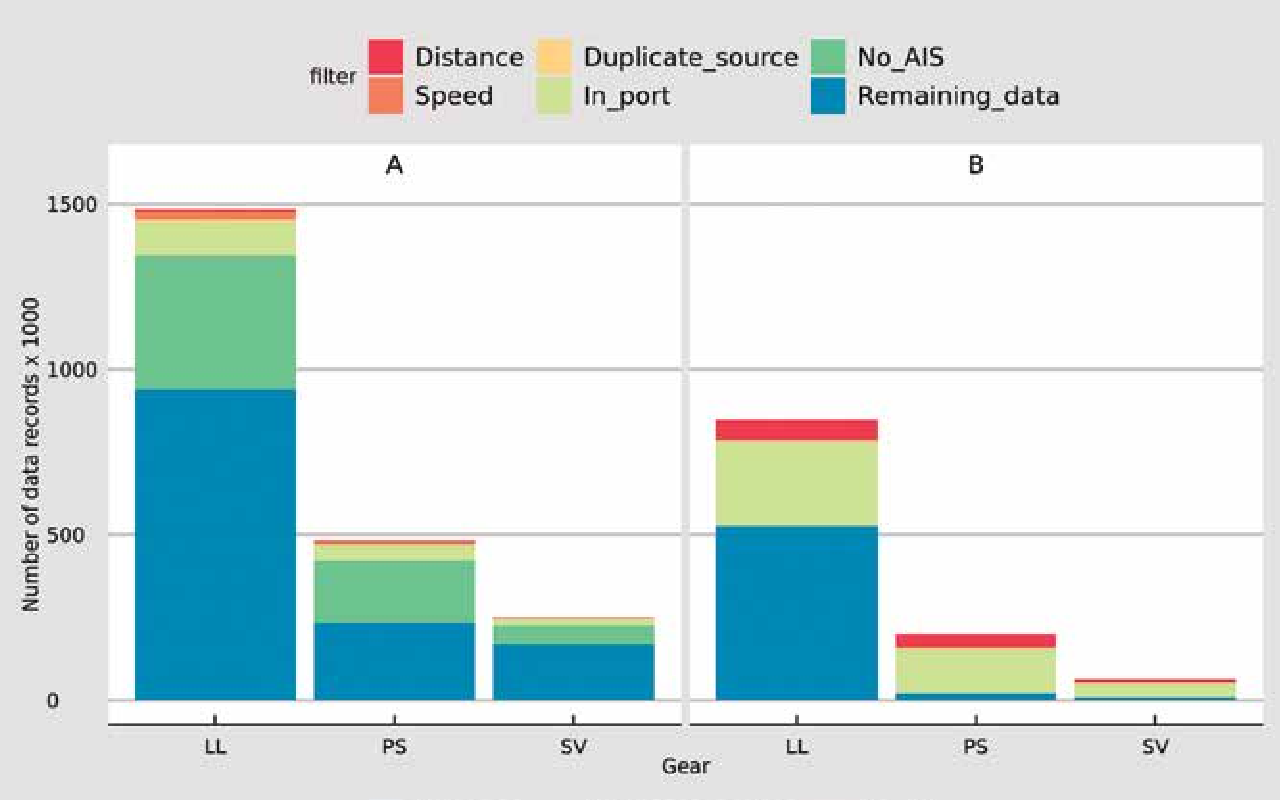

Figure Sey. 2. A) VMS and B) AIS data were filtered for distances < 5 m between transmissions, speed (> 13.5 knots for longliners (LL), > 18 knots for purse seiners (PS), and > 15 knots for supply vessels (SV)), duplicated timestamps due to transmissions received by different satellites or sources, and points within 10 km of a port. Only VMS data that matched AIS MMSIs were retained for further analyses.

METHODS FOR SEYCHELLES COMPARISON

Here, we outline the strategies used to first evaluate if AIS data are representative of the fishing fleet activity by comparing AIS data to VMS data in terms of transmissions and spatiotemporal patterns of vessel trajectories. The spatiotemporal metrics were converted into gear-specific indicators of fishing effort. We finally compared the predictions of fishing activity by the GFW algorithm with known fishing operations from logbook data.

Comparing AIS use and reception to VMS data

Transmissions

Of Seychelles vessels using AIS, about 34 percent were using Class A AIS and about 66 percent were using Class B. Class A systems transmit on average every 2 to 10 seconds while moving and Class B systems generally transmit every 30 seconds and also transmit at lower power, making their messages less likely to be received by satellite (Rec. ITU-R M.1371-5 02/2014) (see introductory sections). Class B systems have lower transmission frequencies when there is a high density of vessels. In terms of data coverage, we compared the quantity of VMS and AIS transmissions over the time period of the study by summing the number of transmissions in a given 1° x 1° grid cell over 2016 and 2017 and for both gears for each data source, consistent with the resolution of the data reported by SFA to IOTC.

Spatiotemporal patterns

Spatial resolution has been shown to be of major importance when estimating the extent of fishing activity from vessel positions (Amoroso *et al.* 2018). The spatial resolution of 0.5° (~50 km) was selected to be consistent with the extent and dynamics of the pelagic fisheries of interest (e.g., vessel speed, longline length, detection range) and finer than that required by IOTC for assessing catch and effort (typically 1°/month for purse seiners and 5°/month for longliners). Further work should however consider finer scales to fully assess the influence of the spatiotemporal resolution on the results.

Thus, vessel positions were overlaid on a 0.5° x 0.5° grid (e.g., Figure Sey. 3). Vessel positions of the filtered VMS and AIS data for longliners, purse seiners and supply vessels were interpolated into trajectories using a maximum time difference of 24 hours between subsequent points. The length of the trajectory within a grid cell was calculated and represents the distance covered by a vessel in that grid cell. Gridded data were aggregated by month for each cell following current IOTC requirements for the temporal resolution of statistical fisheries data and normalized for each data source (i.e., VMS and AIS). The aggregated vessel trajectories then represent the accumulated distance of vessels within each grid cell, which is then a spatial representation of the fleet activity within each grid cell. This can be used to compare the spatiotemporal patterns of AIS and VMS data, and can describe the spatial and temporal patterns of fleet occurrence. Vessel trajectories are later converted to more specific indicators of effort for the purse seine fishery (below, this chapter: Calculating indicators of fishing effort using AIS data).

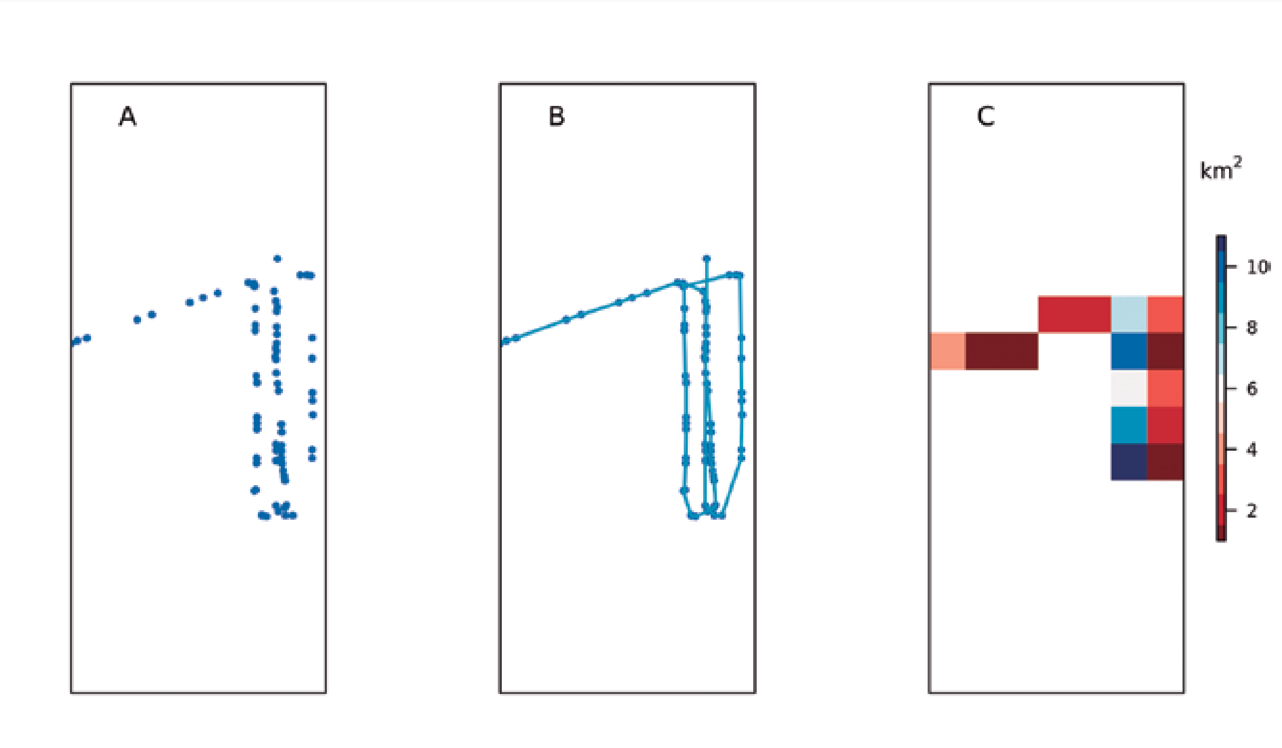

Figure Sey. 3. An example of the trajectory aggregation method using one month of position data. A) Vessel positions given as latitudinal and longitudinal points are B) interpolated into trajectories and then C) overlaid on a grid. Data are then aggregated by averaging the distance of the vessel trajectory within each grid cell over a month. Trajectories like this were then aggregated with trajectories from other vessels within the same time period.

Calculating indicators of fishing effort using AIS data

In fisheries sciences, most assessment methods require time series of abundance indices to inform the trajectories of stock biomass. In tuna fisheries, fishery-independent surveys are almost never available and abundance indices are essentially derived from the analysis of time series of commercial catch per unit effort (CPUE) (Campbell *et al.* 2004). A major prerequisite for the estimation of CPUE is the choice of a unit of fishing effort which aims to reflect the best measure of resources devoted to fishing for a given gear (Cunningham and Whitmarsh 1980).

Nominal fishing effort by purse seiners

For purse seiners, calculations of fishing effort are complex and under continuous evolution; however, nominal fishing effort is generally represented as time at sea and by the number of fishing sets made by a vessel (FAO 2019). As effort is primarily expended by searching for schools, the distance navigated and the surface area that is explored by each vessel can also constitute useful metrics to represent purse seine fishing effort. They could be particularly relevant to account for increased vessel speed and observation range of onboard equipment (e.g., bird radars) over time (Torres-Irineo *et al.* 2014).

Therefore, we use surface area searched by purse seines as a measure of fishing effort. The maximum radar range of detection of bird flocks generally associated with tuna is about 20-25 nm or 37-46 km (Assali *et al.* 2017). This was added as a buffer around the vessel trajectories to incorporate the search zone of the vessel into the total surface area explored by the purse seine vessels. Therefore, the nominal (i.e., not standardised) fishing effort proposed in this study for purse seiners and supply vessels was the surface area searched by the purse seine fleet in each 0.5° x 0.5° grid cell.

Nominal fishing effort by longliners

For longliners, nominal fishing effort is almost always represented as the number of hooks deployed (FAO 2019). Thus, as a measure of nominal fishing effort for longliners, we multiplied the number of fishing days identified by the GFW neural net algorithm (below, this chapter: Comparisons of GFW fishing predictions and logbook entries) by the average number of hooks deployed for each fishing set during 2016-2017 derived from SFA logbooks. To account for spatial differences in fishing practices, we considered a stratification between the area south of 20°S, where Seychelles longliners used on average 3 670 (± 540) hooks to target albacore, swordfish, and oilfish, and the tropical fishing grounds where they used on average 3 000 (± 280) hooks to target bigeye and yellowfin during 2016-2017. GFW-based effort estimates were then compared to logbook-based effort estimates using 1° x 1° and 5° x 5° grid cells, in line with IOTC reporting guidelines.

Comparisons of GFW fishing predictions and logbook entries

The outputs from the GFW neural net algorithm to predict fishing operations were compared to the fishing operations recorded in the official logbooks for Seychelles fleet. Logbook data give the date that a catch was made; neural net data are given at every AIS transmission. Therefore, to compare between the two datasets, we considered a day of fishing to be when there was at least one neural net prediction that indicated fishing (neural net = 1) during the day and we calculated the average position for that day. We then calculated the number of true positives (neural net = 1 at least once during a day that the logbook has an entry), false positives (neural net = 1 at least once during a day that the logbook does not have an entry), true negatives (neural net = 0 for all points during a day and the logbook has no entries), and false negatives (neural net = 0 for all points during a day but the logbook has an entry). Logbook data and neural net predictions were then rasterized to a 0.5° x 0.5° grid. The fishing days in each cell were summed for each year (2016 and 2017) and each gear (longlines, purse seines) and compared using linear regression models. We note that a daily scale is appropriate for longliners as they set once a day; however, purse seiners can set more often. This issue was not investigated further as preliminary results indicated that AIS data are not representative of the purse seine fleet; and thus, the GFW fishing predictions for this fishery are not valid.

RESULTS AND DISCUSSION OF SEYCHELLES CASE STUDY

In general, we find that AIS fleet use and fleet coverage is good for all types of vessels. Overall, we find that AIS data in the longline fleet has good data reception, represents well the spatiotemporal dynamics of the fleet, and have a good ability to predict the actual fishing activity made by longliners. Conversely, we find that AIS data for purse seiners and supply vessels are spatially very poor, with AIS transmissions received only around ports and not in the fishing grounds, making it of little use for further exploration. Thus, having established the utility of the AIS dataset for the different gears, we continue the investigation of longline data only, and compare the calculations of longline effort as derived from GFW data to that of the longline logbooks (both represented as the number of hooks) and find that AIS data can be a useful tool for reporting fishing effort for data-poor fisheries.

AIS fleet use and fleet covered

Fifty-two longliners, 13 purse seiners and 7 supply vessels are listed as active (i.e., have VMS data) in Seychelles official registry for 2016 and 2017 (Table Sey. I). Fourty-three MMSI were provided by GFW for Seychelles longline vessels. Of these, 35 were matched to the official registry of longline vessels that were active in 2016, and 36 were matched to longliners that were active in 2017. Therefore, the fleet use of AIS for 2016 is 74 percent of the 47 vessels active in the longline fishery, and 71 percent of the 51 active in 2017. Ten MMSI were found by GFW for the 13 Seychelles purse seiners, 8 of these MMSI could be matched to vessels active in 2016 (62 percent fleet use of AIS), and 10 could be matched to vessels active in 2017 (77 percent fleet use of AIS). Six MMSI were found by GFW for the 7 Seychelles supply vessels that had VMS data, of which 5 were matched for both years, indicating 71 percent fleet coverage. Reasons for mismatches may be due to the fact that not all vessels have AIS or may have broadcasted incorrect identification information.

Vessel type	Total VMS	Total MMSI	Total GFW AIS	2016				2017			
				VMS	VMS with MMSI	VMS match GFW	% Fleet with AIS	VMS	VMS with MMSI	VMS match GFW	% Fleet with AIS
Longline	52	47	43	47	42	35	74%	52	44	36	69%
Purse seine	13	12	10	13	12	8	62%	13	10	10	77%
Supply vessel	7	7	6	7	7	5	71%	7	7	5	71%

Table Sey. I. Fleet use of AIS data for the vessels with VMS activity in Seychelles fishing fleet for 2016 and 2017. The GFW column indicates the total number of vessels that Global Fishing Watch identified for each fleet for each year. The total active number of vessels with VMS data, the total number of vessels with VMS data that had a MMSI assigned to them, and the number of vessels with VMS data that could be matched to GFW data via the MMSI. The fleet use is calculated as the percent of the total active vessels with VMS data relative to the VMS-to-GFW matched vessels.

Transmission frequency

We found that the transmission frequency of VMS data indicates that both the Seychellois high seas longline and purse seine tuna fishing fleets largely comply with the standard of one transmission per hour, with the predominant peak in transmission frequency at 60 minutes (Figure Sey. 4 - left panel). There are numerous data with transmissions more frequent than this, with another peak in transmission frequency at 10 minutes and the overall median of the data at 22 minutes.

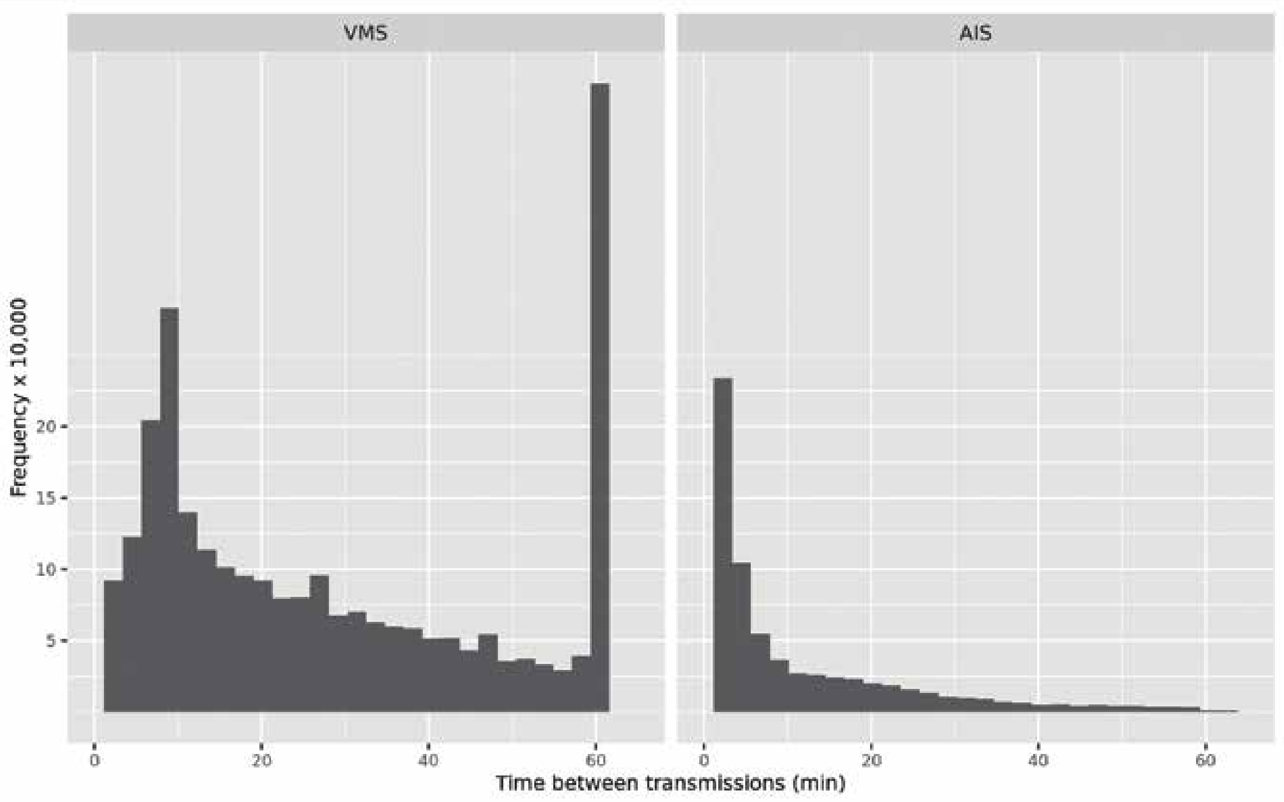

Figure Sey. 4. The frequency of transmissions for (left panel) VMS and (right panel) AIS data for all years and gears combined. Each plot represents the 90th percentile of each dataset.

Spatiotemporal coverage of transmissions by gear

Vessels with AIS were found to transmit their position approximately every 3 minutes (median = 3.1 minutes; Figure Sey. 4 - right panel). Although AIS transmissions were more frequent, we surprisingly found considerably more VMS than AIS transmissions across space and time (Figure Sey. 2; Figure Sey. 5). This may be because many vessels do not broadcast AIS or do not broadcast AIS all the time. The overall spatial trend between VMS and AIS transmissions is similar, but AIS have far fewer transmissions, especially in the Western Indian Ocean (Figure Sey. 5). However, we find more transmissions from AIS than VMS offshore of southern Africa and around the Seychelles, perhaps due to better coastal receiver coverage in these areas. Terrestrial coastal receivers receive messages between 10 to 50 nautical miles offshore (see regional chapter of FAO Area 51).

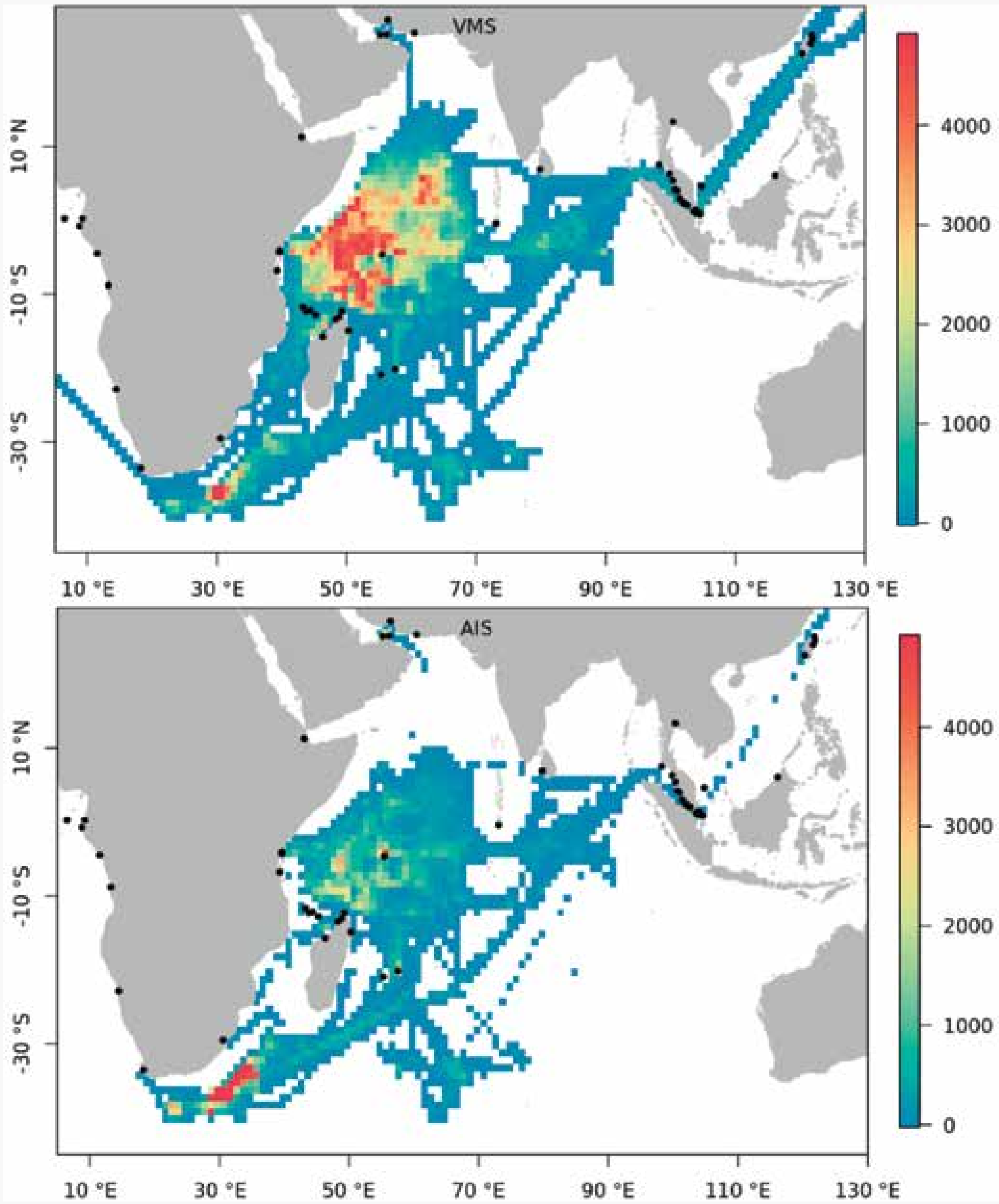

Figure Sey. 5. The number of transmissions per 1° x 1° grid cell for (top panel) VMS and (bottom panel) AIS data for both years and gears combined. Black points represent the ports identified in the study.

Spatiotemporal coverage of transmissions by gear

We found that AIS data match well with the spatial coverage of VMS data for longline vessels, and do not match well for that of purse seiners or supply vessels. AIS for longliners indicate that there is good coverage in the tuna fishing grounds in the Western Indian Ocean (Figure Sey. 6 - top panel). In general, AIS is lacking on the long trajectories made by a few vessels, potentially because AIS may not be in use during long transit periods.

For purse seiners and supply vessels, we found that the majority of AIS positions were transmitted while vessels were in port, and very few positions are transmitted outside of the port zones (Figure Sey. 6 - middle and bottom panel), though there are more AIS reports in the south east in 2017 (Figure Sey. 6 - middle, right panel").

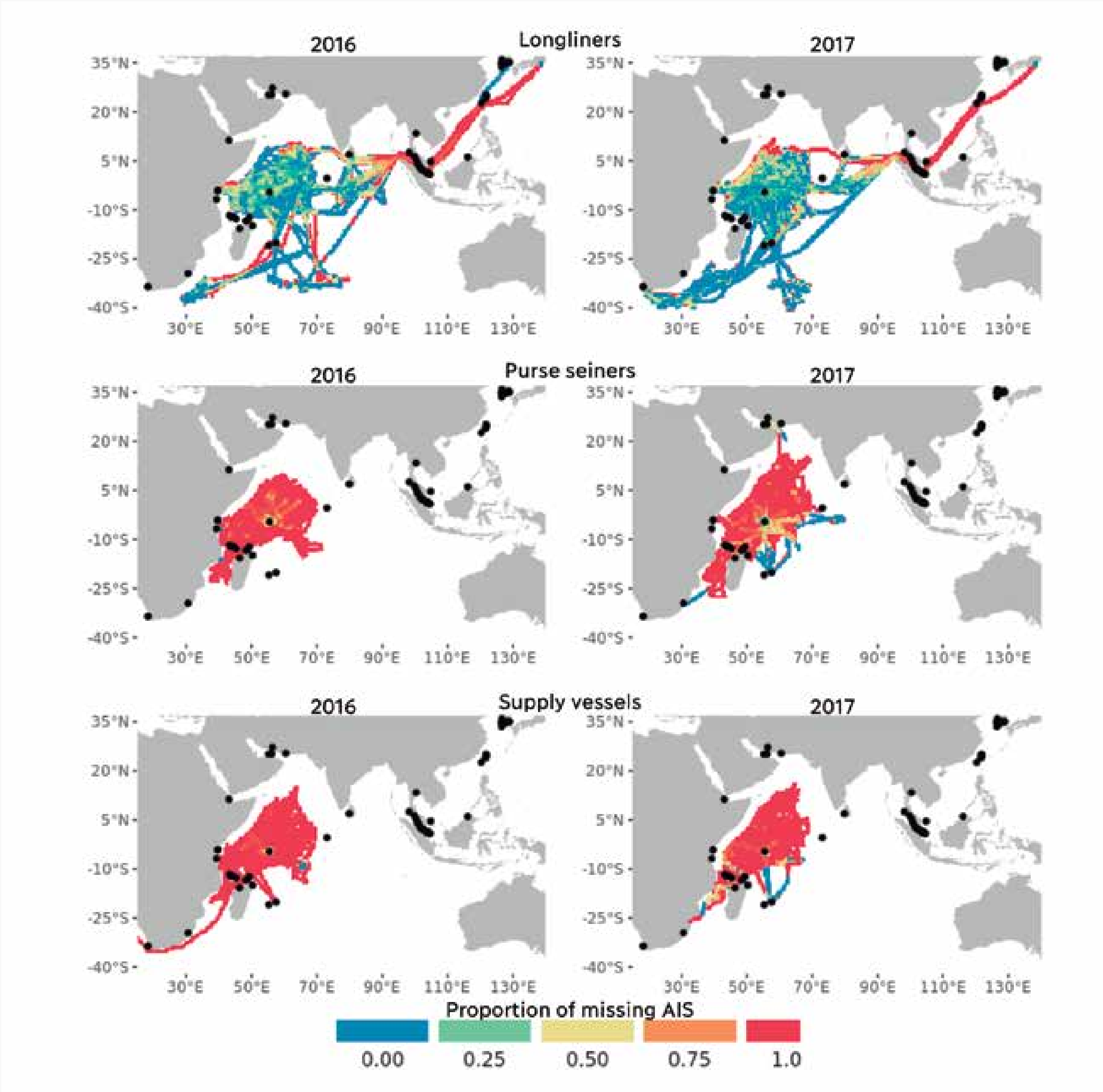

Figure Sey. 6. Spatial coverage of AIS data for (top panel) longliners in 2016 and 2017, (middle panel) purse seiners in 2016 and 2017, and (bottom panel) supply vessels in 2016 and 2017. The color spectrum indicates the proportion of the time when AIS data were available in the cell. Cells towards the red end of the spectrum indicate that no AIS data were available (i.e., AIS always reported NA) and cells towards the blue end of the spectrum indicate that AIS data were always reported. Black points indicate ports.

For longliners, purse seiners and supply vessels, we found that spatial coverage increased gradually over the two years of data (Figure Sey. 7). This may be due to an increase in the number of satellites that received the data (i.e., 15 satellites in 2016, > 50 in 2017; see introductory sections). This increase in satellite coverage is much more likely to affect Class B than Class A AIS transmissions. For the vessels broadcasting Class A, gaps in activity are most likely explained by vessels turning off their AIS. For Class B, poor reception may explain some of the data lacking in the northern fishing grounds (see map in chapter on FAO Area 51); and increased satellite coverage may explain some of the cells with a higher proportion of AIS use in 2017. Further analysis is needed to determine if the spatial variability of reception is due to reception or the systems being turned off.

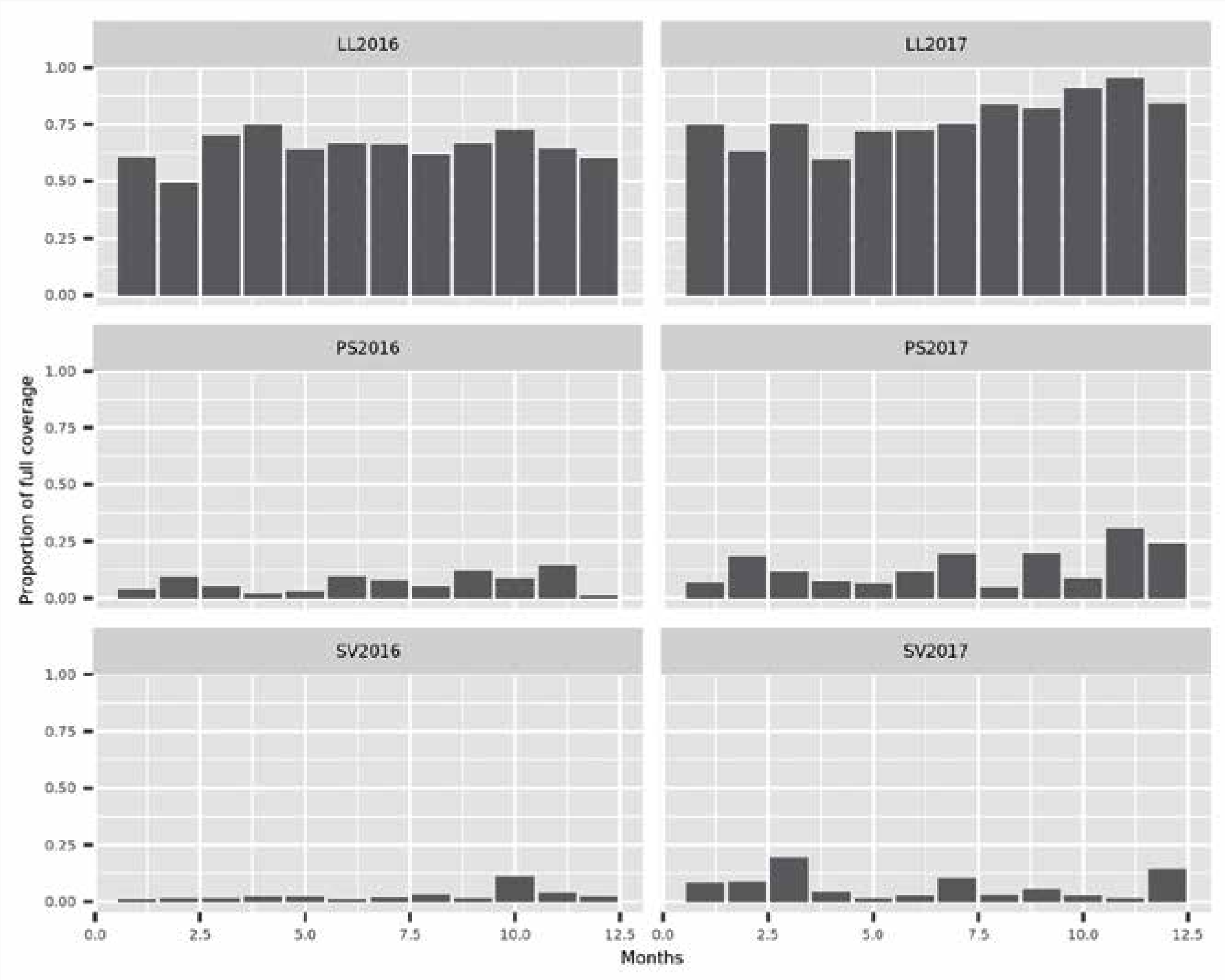

Figure Sey. 7. The monthly proportion of AIS spatial coverage relative to the full spatial coverage of AIS and VMS data combined for (top panel) longliners (LL) in 2016 and 2017, (middle panel) purse seiners (PS) in 2016 and 2017, and (bottom panel) supply vessels (SV) in 2016 and 2017.

AIS switch-off in the purse seine fleet

Our findings indicate that there is a high likelihood of considerable AIS switch off, particularly for the purse seine fleet and their supply vessels. This is supported by the fact that AIS data are transmitted at a maximum of around 25 percent of VMS data (Figure Sey. 7) and that these transmissions are essentially only in the port region (Figure Sey. 6). Furthermore, AIS transmissions are consistently and substantially lower in quantity than VMS data (Figures Sey. 2,4,5,6,7), even though the frequency of transmissions is much higher (Figure Sey. 4). This is evident for both longline and purse seine fleets (and supply vessels), but it is particularly pronounced for purse seiners. Concerns over safety due to piracy in the Western Indian Ocean starting in 2007-2008 (Chassot *et al.* 2010) led to purposeful AIS switch off once outside the port region following security recommendations of the counter-piracy military operations occurring in the region (e.g. Atalanta). Though piracy was less of a concern during the study period than previously, this switch-off behavior appears to continue for the purse seine fleet as part of the standard measures put in place by onboard private security companies.

The difference in the nature of the fishing activity between longliners and purse seiners may also play a role in this switch-off behavior. Longliners use a passive fishing gear, which consists of deploying a baited line and hauling it in several hours later. In contrast, purse seiners actively search for schools and their activity comes with a high risk of failure to catch, e.g. about a 50 percent failure rate for free-swimming schools. This failure comes at a cost, as it takes about 1.5 hours to retrieve a purse seine once it has been set, and if there is another purse seiner in the vicinity, it will approach the first vessel in an attempt to catch the school that the first vessel may have failed to catch. In addition, tuna schools can concentrate in very large abundances in some areas over several days (e.g., Fonteneau *et al.* 2008). Therefore, detecting a purse seiner in operation is not only an indication of tuna presence but it can also be rewarding if there is a high concentration of tuna whereby the vessels will be able to make several operations in a row, sometimes over several days. Finally, with the recent emergence of FADs equipped with echo-sounders, the presence of a purse seiner or of a supply vessel in an area now strongly indicates the detection of tuna around the FAD. In short, the presence of a longliner suggests there might be some tuna in an area while the presence of a purse seiner in operation indicates there are tuna in an area. Thus, purse seiners are likely more motivated to keep their position private by switching off their AIS than longliners.

Spatiotemporal comparisons of AIS and VMS fleet activity

Surface area explored by purse seiners and supply vessels

The surface area explored by purse seiners and supply vessels, as calculated using a buffer around the aggregated trajectories for VMS data, indicates that there are high rates of exploration in the areas to the northeast and southwest of Seychelles, in line with the known fishing grounds of the purse seine fleet (e.g., Figure Sey. 8 - top left panel). As there are very few AIS data for purse seiners and supply vessels outside of port, the surface area explored by these vessels using AIS data offers little useful information (e.g., Figure Sey. 8 - top right panel).

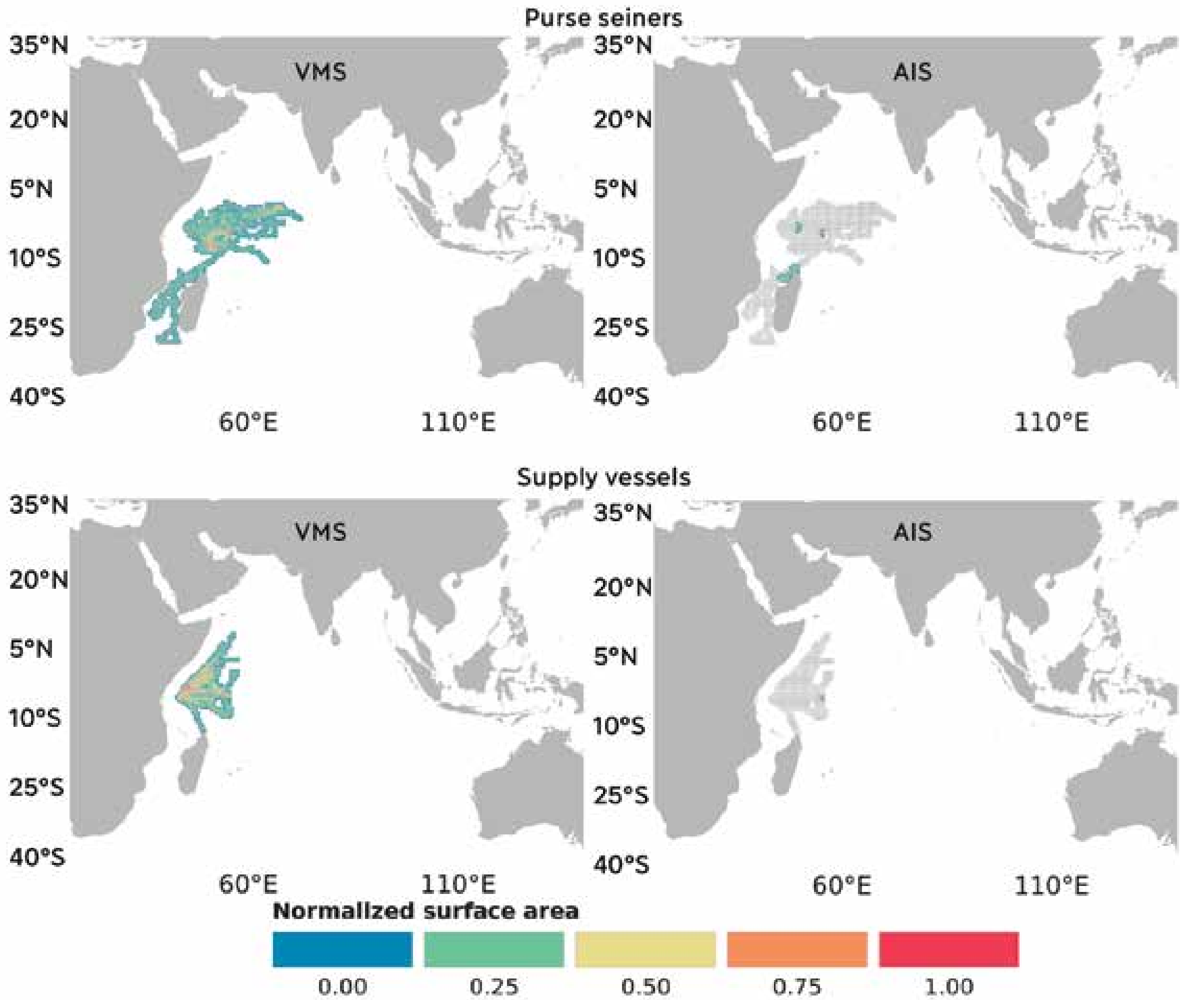

Figure Sey. 8. The normalised surface area explore by Seychelles purse seiners and supply vessels in May 2017 as calculated by determining the surface area from the length of the vessel trajectories with a buffer of 38 km around the trajectory. Surface area is aggregated over the month for each cell for VMS and AIS data of (top panel) purse seiners and (bottom panel) supply vessels. Light grey indicate missing data.

Distance covered by longline vessels

We find that AIS data for the distance covered by longline vessels as calculated from the aggregated trajectories matches well with that calculated using VMS data (e.g., Figure Sey. 9). The spatial pattern is very similar, indicating that vessels spend the majority of their time in the tropical Western Indian Ocean. AIS generally show lower magnitude values than VMS data for the distance covered by vessels. This is due to VMS data having fewer and longer trajectories because they continuously record data with few pauses between transmissions of > 24 hours, whereas AIS data have many but short trajectories due to frequent breaks in transmission > 24 hours (e.g., Figure Sey. 10).

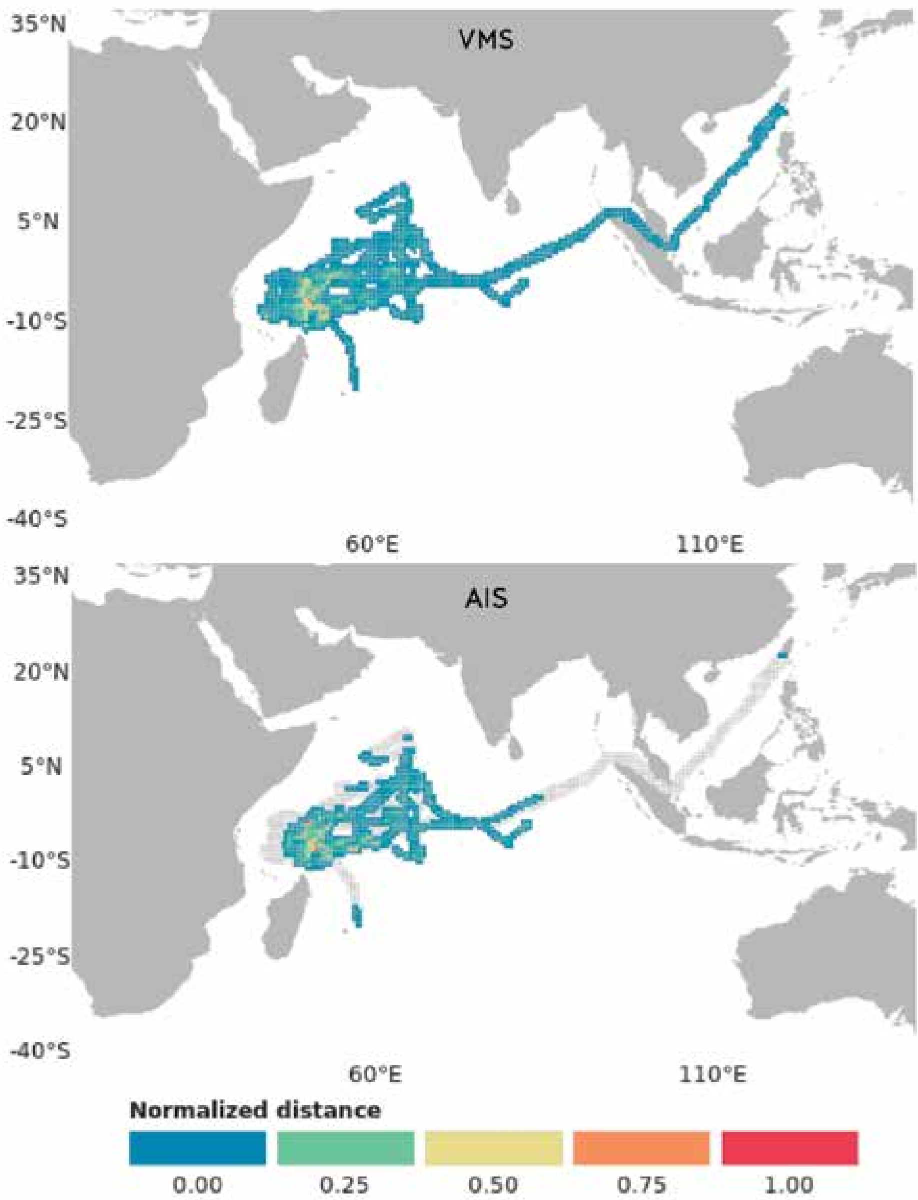

Figure Sey. 9. The normalized distance covered by Seychelles longliners in January 2016 as calculated by the length of the vessel trajectories within each 0.5° x 0.5° cell aggregated over the month for (top panel) VMS and (bottom panel) AIS data. Higher values indicate that more distance was covered in a cell. Light grey indicate missing data.

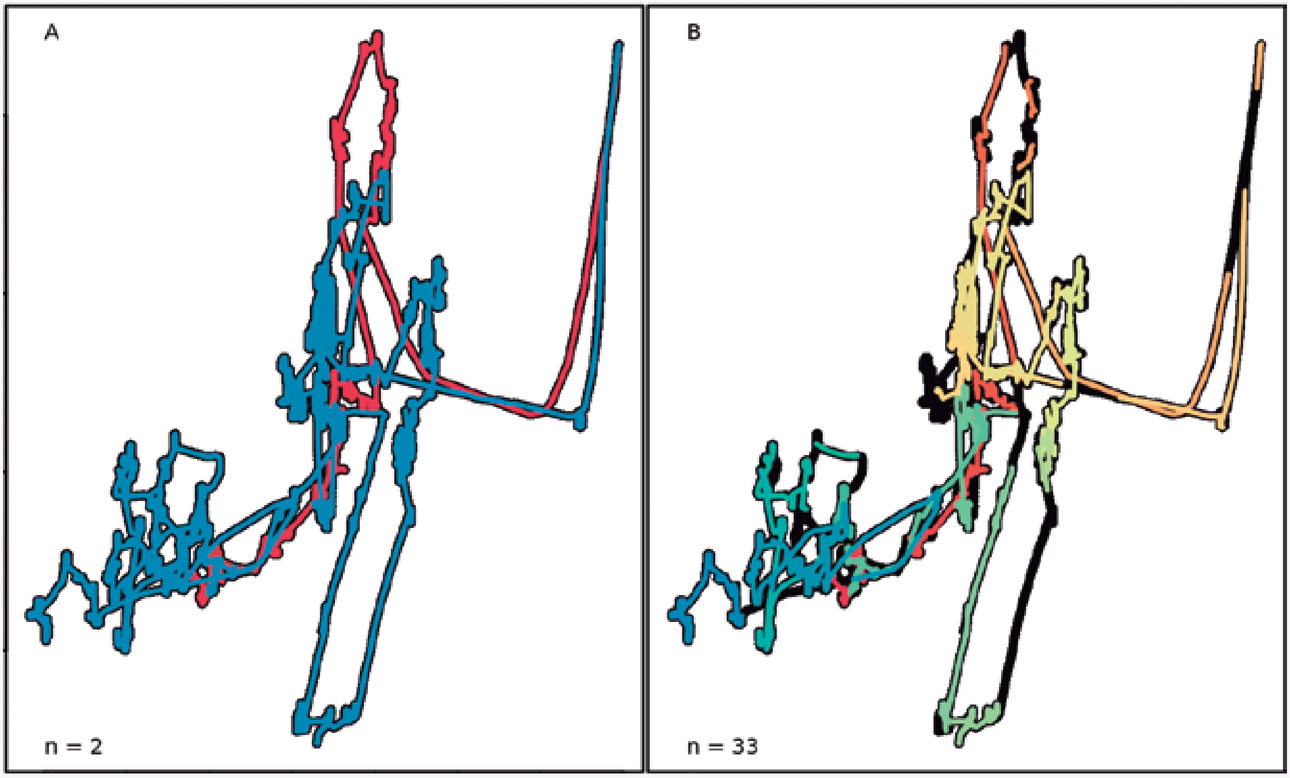

Figure Sey. 10. An example of trajectories calculated from one longline vessel to compare the difference in length and number VMS versus AIS trajectories. Black points on both plots are VMS transmissions. The different colored lines overlaid on the points represent different trajectories from A) VMS data (N trajectories = 2) and B) AIS data (N trajectories = 33). A trajectory is defined as a continuous transmission with breaks between transmissions < 24 hours. AIS points were overlaid on the VMS data in B) to show where the AIS data were and were not, considering VMS as the reference dataset.

Accuracy of GFW algorithm performance for predictions of fishing activity compared to reported fishing activity from logbook data

We find that the GFW neural net algorithm is able to predict days of fishing relative to logbook data (i.e., correctly predicted fishing days) for longline vessels between 45.3 percent of the time in 2016 to 70.5 percent of the time in 2017, and has very low prediction rates for the purse seine vessels (Table Sey. II).

Longliners

For longliners, days where GFW correctly predicts that no fishing occurred happened 91.4 percent (2016) and 96.5 percent (2017) of the time. Days where GFW incorrectly predicted that fishing occurred when the logbook indicated no fishing were found 19.4 percent of the time in 2016 and 36 percent of the time in 2017. Days where GFW did not predict fishing, but logbooks indicate catch, were found 8.6 percent (2016) and 3.5 percent (2017) of the time. In general, we find that fishing predictions are higher in 2017 than in 2016, including correct predictions of both fishing and non-fishing days, coinciding with better satellite coverage.

Longline 2016 **N=6988, M=4130**		AIS GFW algorithm		**Purse seine 2016** **N=2374, M=16**		AIS GFW algorithm	
		Fishing	No fishing			Fishing	No fishing
Logbook	Fishing	45.3%	8.6%	Logbook	Fishing	0.7%	2.9%
	No fishing	19.4%	91.4%		No fishing	0.4%	97.1%
Longline 2017 **N=6265, M=4488**		Fishing	No fishing	**Purse seine 2017** **N=2623, M=40**		Fishing	No fishing
Logbook	Fishing	70.5%	3.5%	Logbook	Fishing	1.5%	3.0%
	No fishing	36.0%	96.5%		No fishing	1.0%	97.0%

Table Sey. II. The accuracy of the predictions of days of fishing by the neural net algorithm provided by GFW for the longline and purse seine fleets in 2016 and 2017. GFW accuracy is calculated as the percentage of either fishing (neural net = 1) divided by the total number of fishing days from logbook data (N) or no fishing (neural net = 0) divided by the total number of days where no fishing was recorded in the logbooks. Green cells indicate true predictions and red cells indicate false predictions made by the GFW neural net algorithm. M indicates the total number of fishing days predicted by the GFW algorithm (i.e., where the neural net = 1).

The spatial patterns of the positions where the neural net algorithm indicated fishing and the positions recorded in the logbook are similar overall for longliners, though results show a high variability between grid cells (Figure Sey. 11 - top panel). Looking at the percent difference between logbook sets and GFW predictions of daily fishing activity (i.e., ($Sets_{logbook}$-$Sets_{gfw}$)/$Sets_{logbook}$, Figure Sey. 11 - middle panel), we find that GFW neural net predictions show many good predictions (differences near 0), with about 50 percent of the points underpredicted by GFW (differences greater than 0). The linear regression of logbook fishing sets versus neural net predictions of days of fishing indicates a good relationship for both 2016 (r^2 = 0.55) and 2017 (r^2 = 0.89). However, it is worth noting that the coefficient of determination is biased due to the spatial autocorrelation of the data. We find that the neural net algorithm of daily fishing activity consistently underestimates the logbook sets by about 60 percent in 2016 (slope of the linear model = 0.39), and about 15 percent in 2017 (slope of the linear model = 0.85). Consistent with Table Sey. II, we find better predictions in 2017 than 2016 (Figure Sey. 11 - middle and bottom panel).

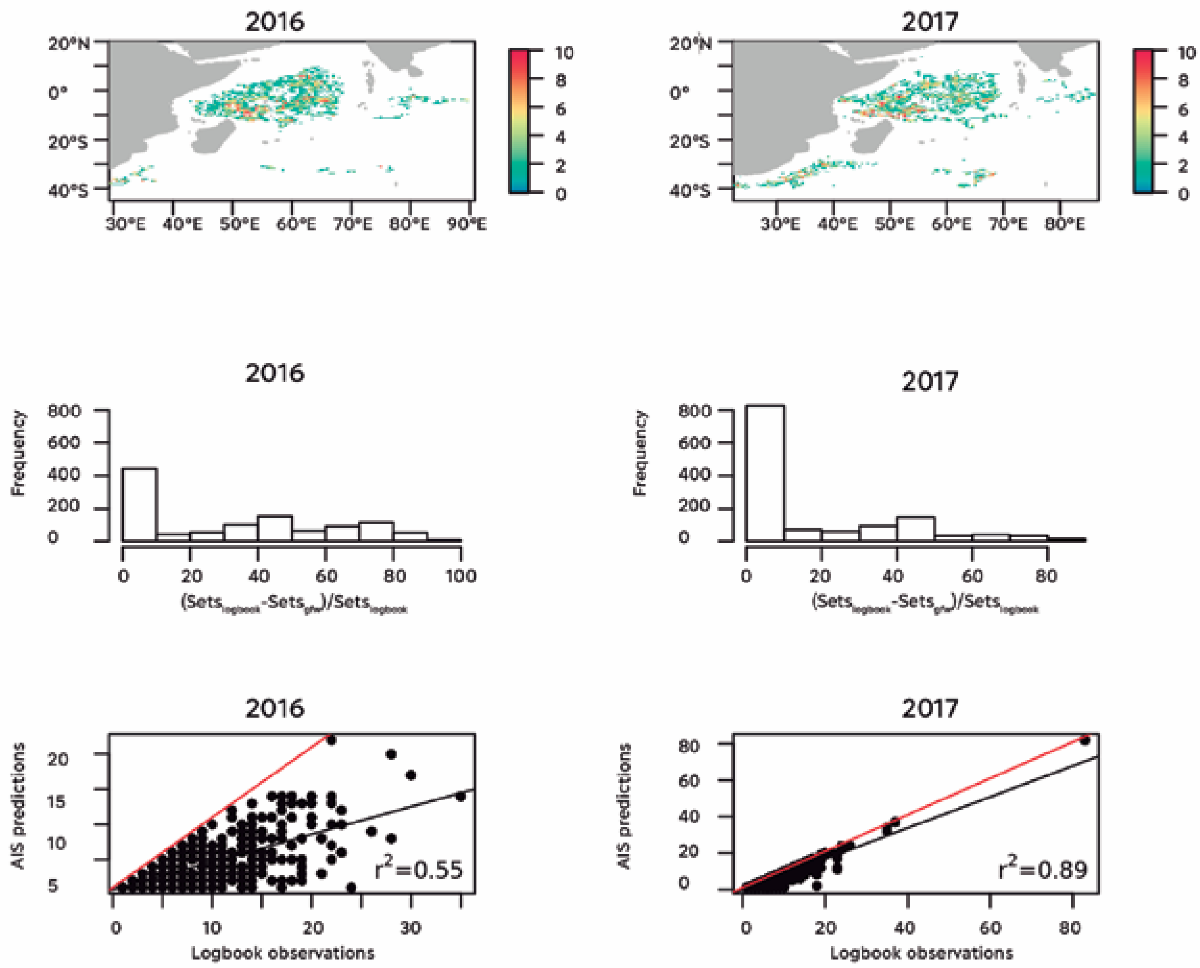

Figure Sey.11. Positions where the GFW neural net algorithm predicts a day of fishing to occur for longline vessels in 2016 and 2017 (top panel) on a 0.5° x 0.5° grid with fishing days summed over the period within each cell; the percent anomaly between coincident logbook data and the GFW predictions ($Sets_{logbook}$-$Sets_{gfw}$)/$Sets_{logbook}$) for 2016 and 2017 (middle panel), and linear regressions of the relationship between logbooks and GFW predictions for 2016 and 2017 (bottom panel).

When comparing the true positive positions where the neural net algorithm predicts fishing on the same day as the logbook has a record (i.e., the daily mean position when a true positive fishing was detected), we find that the distances between the AIS true positive positions and the positions of longliner logbook sets are relatively close, i.e., 75 percent of the AIS points are within 50 km of the logbook points (Figure Sey. 12 - top panel). As individual longlines can be up to 100 km in length, these values indicate that the spatial distribution of the true positive points are representative of the logbook data.

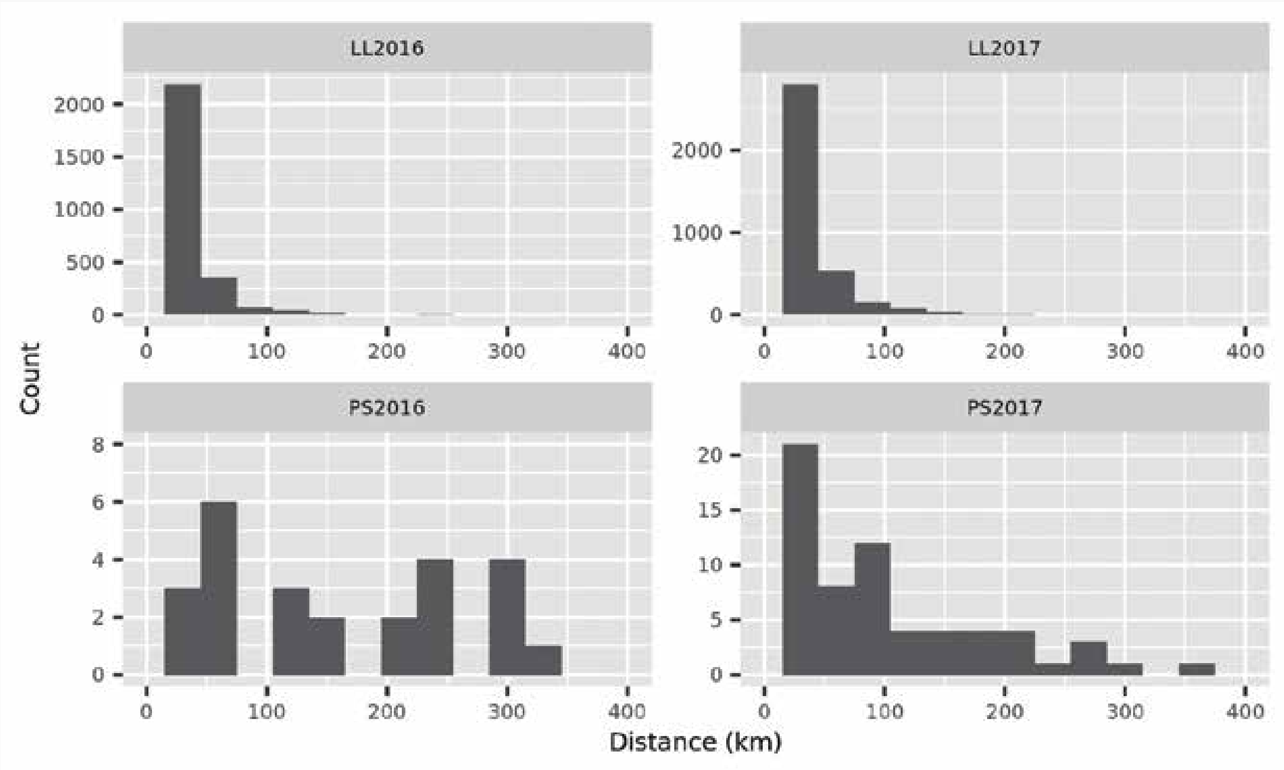

Figure Sey. 12. Distance (km) between logbook positions and AIS true positive fishing positions as predicted by the GFW neural net algorithm for (top panel) longliners and (bottom panel) purse seiners in 2016 and 2017.

We investigated the hour of the day in which the GFW neural net algorithm predicted fishing operations (all predictions, not limited to true positives), and found that for longline fishing, the predictions were reasonable (Figure Sey. 13 - top panel). The algorithm indicates that the majority of fishing occurs during two periods, in the morning (from 05:00 to 10:00) and in the evening (16:00 to 20:00). This corresponds to fishing practices of Seychelles longliners as longlines targeting tuna in the western-central Indian Ocean are generally set during the day and hauled in the evening and longlines targeting albacore, swordfish and oilfish south of 20°S off the coasts of South Africa are generally set at night and are hauled in the morning.

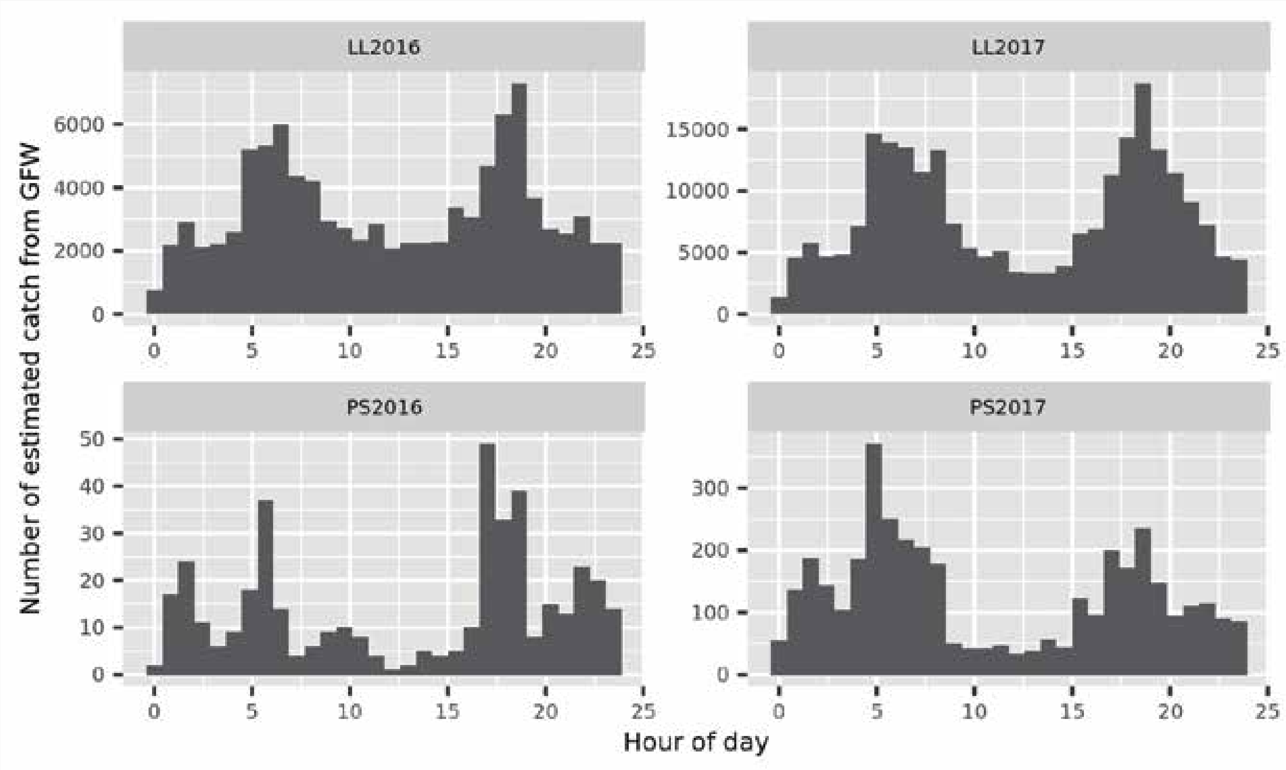

Figure Sey. 13. Hour of the day in which the GFW neural net algorithm identifies fishing for (top panel) longliners and (bottom panel) purse seiners in 2016 and 2017.

Purse seiners

There are few AIS data for purse seiners outside of the 10 km diameter around ports. Of those data that are available, very few are in regions where purse seine fishing is possible (> 200 m depth). The neural net algorithm does well in that it correctly predicts 'No fishing' for most of these data points, but only correctly predicts when fishing does occur less than 2 percent of the time in both 2016 and 2017 (Table Sey. II).

Very few AIS positions for purse seiners are reported in the fishing grounds. For those positions that are available, when comparing AIS positions where GFW predicted true positive fishing activity with the positions of purse seine logbook sets (i.e., daily mean positions), we find that 75 percent of the AIS points are at a distance of 200 km of the logbook points (Figure Sey. 12 - bottom panel). As purse seiners set their nets at a radius of ~500 m from the vessel, we find that the distance between the majority of AIS true positive predictions and logbook positions is far greater than that of a purse seiner set. This indicates that the true positive predictions of the GFW algorithm may not actually represent the logbook set for that day, i.e., the true positive predictions for purse seiners made by GFW may be a result of chance.

When considering the hours during which fishing is predicted for purse seiners, the results seem unlikely. Purse seine nets are only set during the day and the vessels do not fish at night; however, we find that the neural net algorithm makes predictions of fishing operations during hours of darkness, i.e., 20:00 to 04:00. This might instead correspond to the vessel being stopped and drifting at night (Figure Sey. 13 - bottom panel).

Indicators of longline fishing effort using AIS data

Based on the results above, it was deemed that for purse seiners and supply vessels AIS data do not show spatiotemporal coherence with VMS data in terms of either reception or fleet activity. Therefore, these data were not considered further in this study. However, for longliners, the spatiotemporal patterns of reception and fleet activity derived from AIS data showed good correspondence to that derived from VMS data; and GFW predictions of fishing activity are also reasonably coherent to allow further investigation.

Longline fishing effort as the number of hooks

Therefore, we correlated the estimations of longline effort derived from GFW predictions of fishing sets against the spatially aggregated effort reported by SFA to the IOTC, both of which are represented as the number of hooks deployed by longline vessels (see above, this chapter: Calculating indicators of fishing effort using AIS data). In each year, there is a strong linear relationship (the coefficient of determination, r^2, varies between 0.61 and 0.95) between the predicted GFW effort and the effort reported in logbooks aggregated for each grid cell (Figures Sey.14-15). As with GFW predictions of daily fishing activity, effort calculated using GFW predictions consistently underestimates the actual effort reported by logbooks by about 63 percent (slope of the linear model = 0.37) in 2016 to about 18 percent (slope of the linear model = 0.82) in 2017 for a 1° x 1° grid. These underestimations may be due to issues with AIS reception. Also, the predictions appear inconsistent for many grid cells, especially when considering a 1° x 1° spatial resolution (Figure Sey. 14). The fit to the data was improved between 2016 and 2017, i.e. r^2 increases from 0.61 to 0.92 for the 1° x 1° grid and from 0.81 to 0.95 for the 5° x 5° grid between 2016 and 2017, respectively. The larger spatial resolution of the 5° x 5° grid substantially improves the correlation and decreases the variability from that observed with the 1° x 1° grid (Figure Sey. 15).

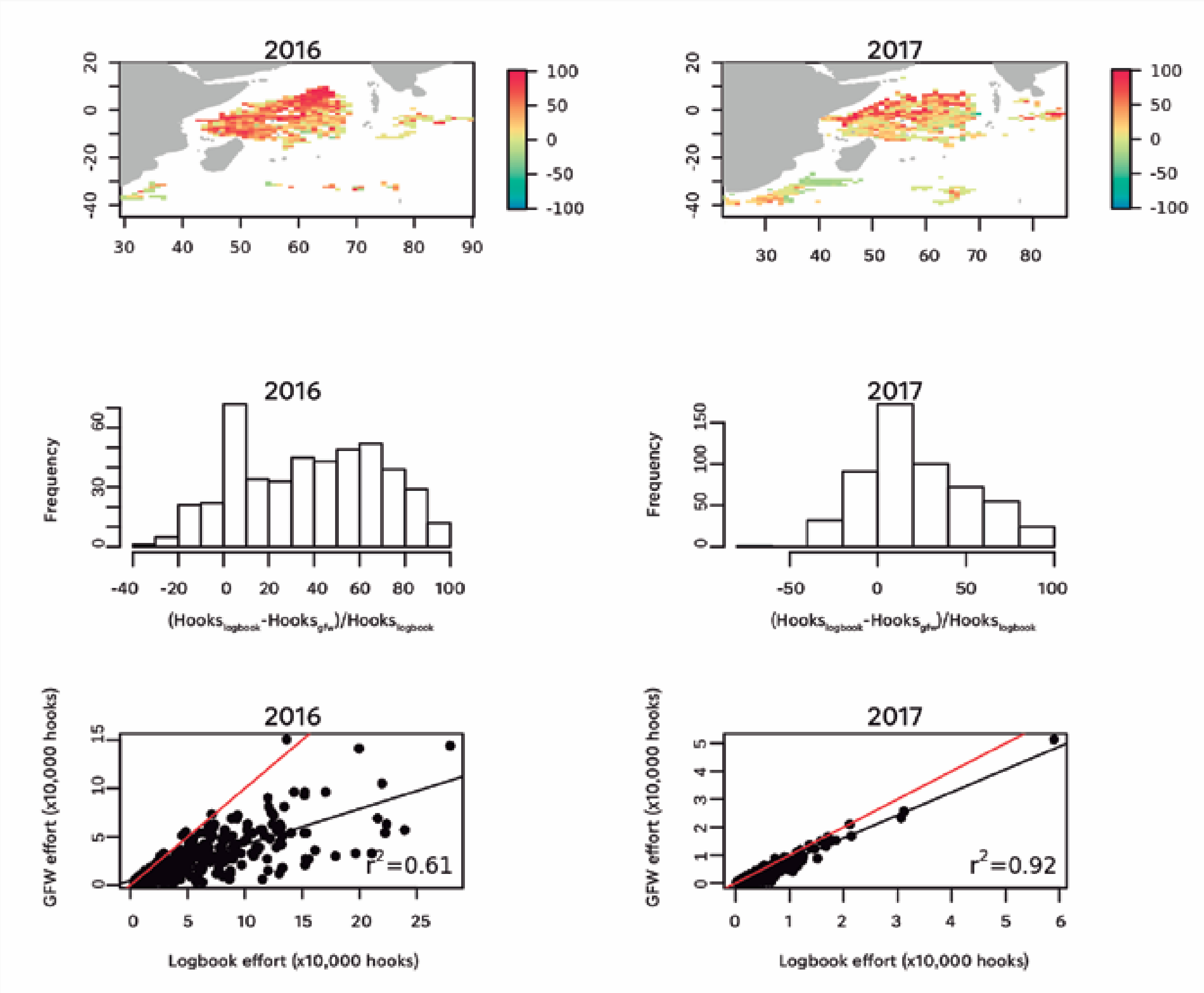

Figure Sey. 14. Normalised anomaly maps of longline fishing effort (hooks) calculated as the number of logbook hooks minus the number of GFW hooks on a 1° x 1° grid, normalised by the number of logbook hooks for 2016 and 2017 (top panel); the distribution of the normalised anomaly of fishing effort between logbooks and GFW for 2016 and 2017 (middle panel), and the linear relationship between logbook effort and GFW effort for (bottom panel).

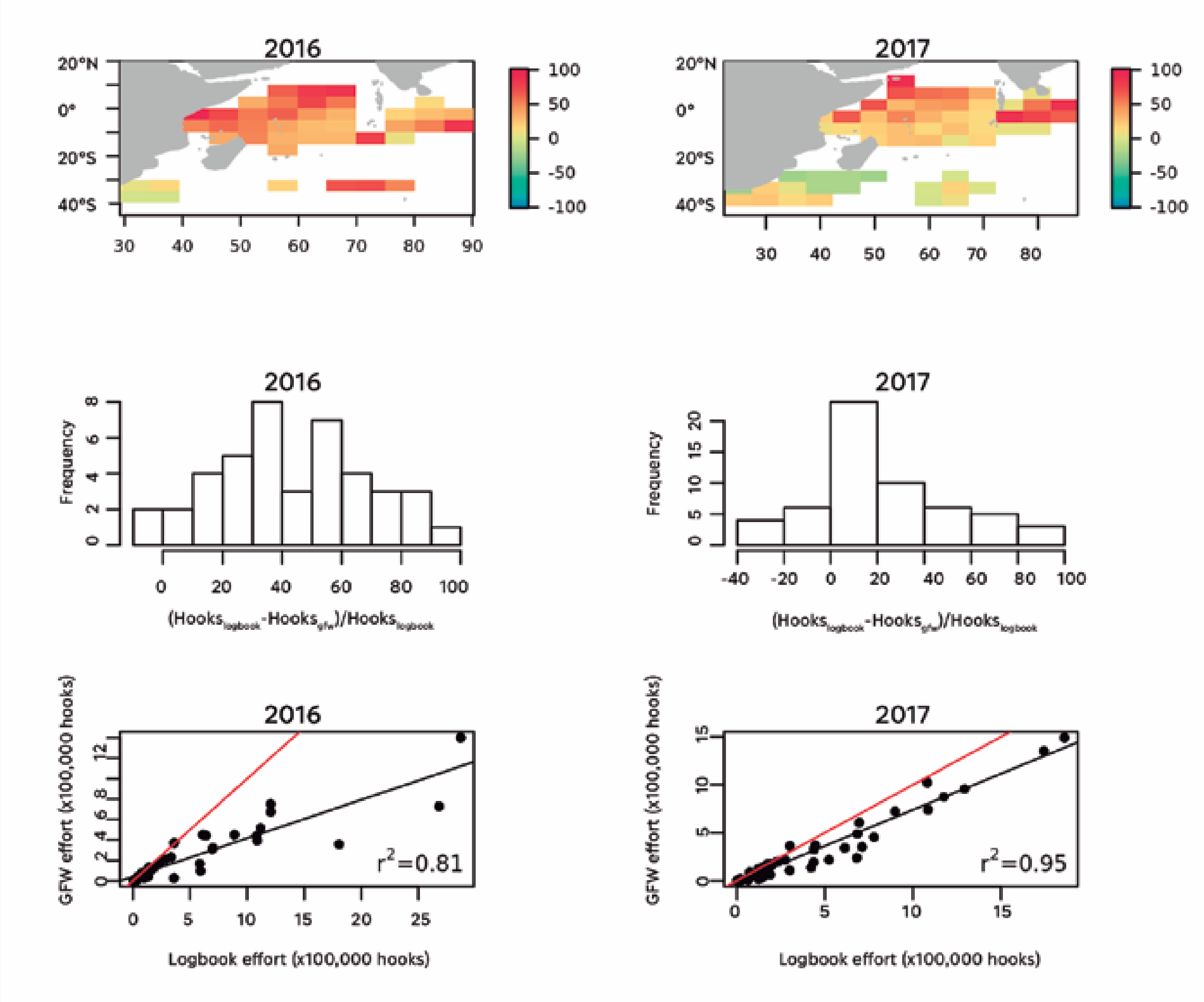

Figure Sey.15. Normalised anomaly maps of longline fishing effort (hooks) calculated as the number of logbook hooks minus the number of GFW hooks on a 5° x 5° grid, normalised by the number of logbook hooks for 2016 and 2017 (top panel); the distribution of the normalised anomaly of fishing effort between logbooks and GFW for 2016 and 2017 (middle panel); and the linear relationship between logbook effort and GFW effort for 2016 and 2017 (bottom panel).

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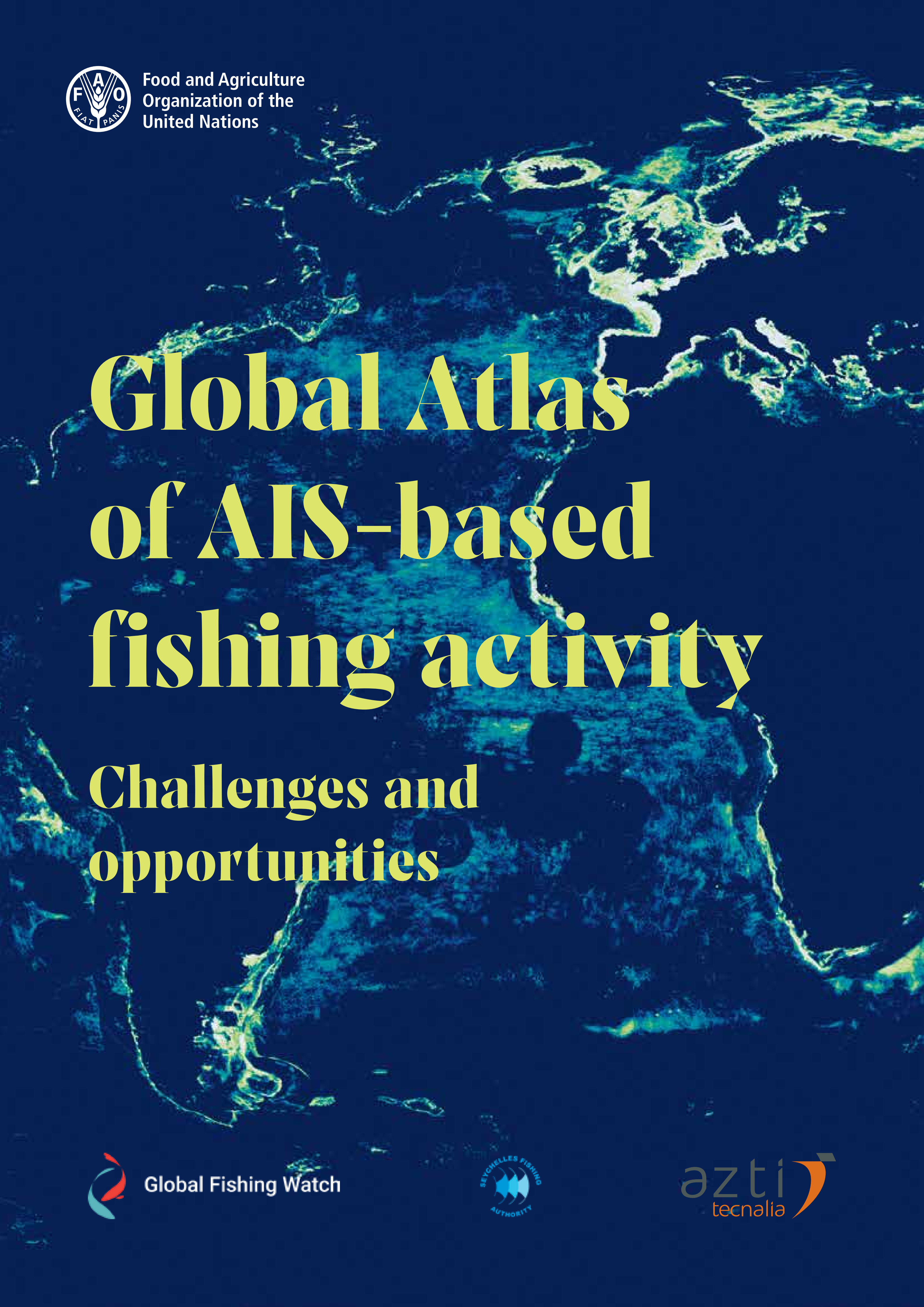

Global Atlas of AIS-based fishing activity

Challenges and opportunities

Global Fishing Watch

SEYCHELLES FISHING AUTHORITY

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Global Atlas of AIS-based fishing activity

Challenges and opportunities

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