Potential applications and methodologies for AIS use in Seychelles deep-water tuna fisheries

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Introduction

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 spatio-temporal resolution allowed calculations of effort using 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 (REF to previous chapter), the temporal resolution of monitoring has been further refined from hours to minutes or seconds (Robards et al. 2016). 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). 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 is interested in investigating the potential of AIS for monitoring vessels, detecting fishing activities, and calculating fishing effort. Seychelles is a regional leader of marine stewardship in the western Indian Ocean. The Seychelles government is currently developing a Management Spatial Plan (MSP) that will protect 30% of its exclusive economic zone (EEZ) from fishing and extraction activities by 2020 (**Figure 1**). In addition, the Seychelles are involved in the joint management with Mauritius of adjacent closed regions[1]. In order to implement effective management plans, monitoring and compliance measures need to be at a commensurate level. Since the early 2000s, VMS in the Seychelles has been well maintained and closely monitored for vessels >12 m, but there are numerous smaller vessels that are not monitored. The high resolution of AIS data could be

[1] http://www.un.org/depts/los/LEGISLATIONANDTREATIES/STATEFILES/SYC.htm

of interest for monitoring small-scale displacements of fishing vessels within MSP areas. In addition, while AIS data are publicly accessible, VMS data are confidential and only available at a national level. Therefore, data for non-Seychellois vessels are not accessible outside the Seychelles EEZ, i.e. for some vessels occurring in the joint management area.

Here, we investigate the difference between AIS data provided by GFW and the VMS and logbook data for the Seychelles deep-water tuna fishery, comprising both industrial purse seine and drifting longline vessels. It is noteworthy that the Seychelles purse seine fleet also includes some non-fishing support vessels that substantially contribute to the effort by searching for tuna schools and maintaining the array of Fish Aggregating Devices (FADs) used for increasing purse seiners' catchability (Assan et al. 2015). VMS in the Seychelles are continuously and rigorously monitored by the Seychelles Fishing Authority (SFA), making it a highly reliable source of information of industrial fishing vessel activity. On the contrary, there are no specific mandates or requirements of AIS for Seychelles fishing fleets. The majority of vessels that use AIS have been equipped for safety according to IMO legislation[2]. In a first step, we investigate how well AIS data cover the Seychelles industrial tuna fishing fleets and represent their spatio-temporal patterns of occurrence. In a second step, estimates of fishing activity based on GFW predictions are assessed against information collected from fishers' logbooks. Furthermore, we investigate the potential of AIS data for use in deriving fishing effort for these fisheries in the more general context of tuna monitoring and management by the Indian Ocean Tuna Commission (IOTC).

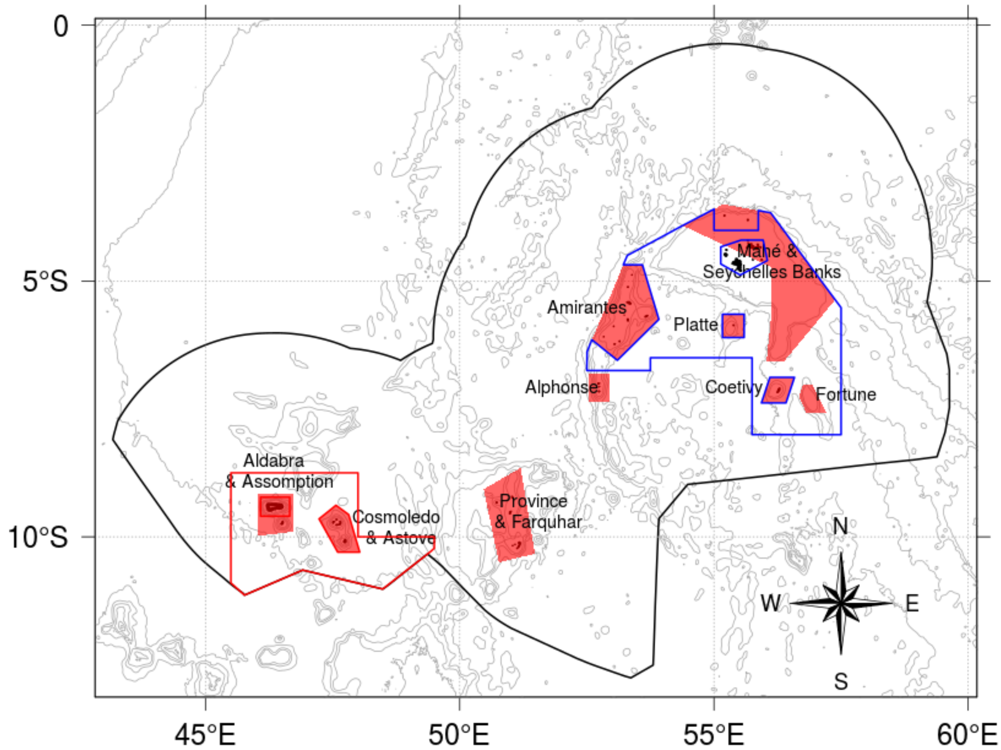

Figure 1 The exclusive economic zone (EEZ) of the Seychelles (black line), located in the western Indian Ocean, with the marine protected areas identified as part of the Fisheries Act (red polygons) and Management Spatial Plan. Red solid line = No-take area; Blue solid line

[2] http://www.imo.org/en/ourwork/safety/navigation/pages/ais.aspx

= Sustainability use area (i.e., regions where there is low-level non-industrial use of resources that are in line with nature conservation).

Data and Methods

Fishing fleets

The Seychelles purse seine fleet is made up of 13 foreign-owned vessels (~90 m long) and 7 support 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% of fishing occurring in the Seychelles exclusive economic zone (EEZ; **Figure 1**). Purse seines generally deploy in waters >200 m (i.e. off the continental shelf), and can target schools between 50 m to 150 m depth. In recent years, this fleet has taken in annually >100,000 mt of primarily skipjack (*Katsuwonus pelamis*) and yellowfin tuna (*Thunnus albacares*), the majority of which is destined for the cannery. Fishing effort for purse seines is generally represented as time at sea, or by the number of sets made by a vessel. As effort is primarily expended by searching for schools, a useful metric to represent purse seine fishing effort would be a measure of the surface area explored by each vessel.

The Seychelles longline fleet is made up of 49 vessels (~50 m long), owned by locally-operated Taiwanese companies that access Seychelles waters via fishing agreements. This fleet fishes yellowfin and bigeye tuna (*Thunnus obesus*) in the western equatorial region with about 35% of fishing occurring in the Seychelles EEZ. To a lesser extent, this fleet also targets albacore tuna (*Thunnus alalunga*) and swordfish (*Xiphias gladius*) in the southwestern Indian Ocean near South Africa. Total catch is about 11,000 mt, most of which is destined for the sashimi market. Vessels offload their catch in the ports of Durban, South Africa, or Port Louis, Mauritius. Vessels also transfer their catch at sea during transshipments; all transfers are required to be observed by the Regional Observers Program of the IOTC (Res. 14/06). Fishing effort for longline vessels is typically represented by the number of hooks deployed at sea.

Data sources

AIS data for 2016 and 2017 were provided by GFW. Data were extracted specifically for drifting longliners, purse seiners, and support vessels of the Seychelles industrial tuna fishery, identified via their maritime mobile service identities (MMSI). AIS data were available for 35 longline vessels in 2016, 36 in 2017; eight purse seine vessels in 2016, and 10 in 2017; five supply vessels in 2016 and 2017 (Table 1). 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 (REF to previous chapter). Neural net scores are given as either 0 (no fishing) or 1 (fishing).

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 time stamps 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 to 44 of the 51 longline vessels in the Seychelles fleet, 12 out of 13 purse seiners, and seven out of seven supply vessels (Table 1).

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. Logbooks also provided information on the effort of each set, including the number of hooks deployed for each fishing set for longliners and the hours at sea for purse seiners during daylight as these vessels do not operate at night.

Table 1. Fleet coverage of AIS data for the vessels with VMS activity in the 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 coverage is calculated as the percent of the total active vessels with VMS data relative to the VMS-to-GFW matched vessels.

Fishery	Total GFW	2016				2017			
		VMS Total Active	VMS with MMSI	VMS match GFW	Fleet coverage	VMS Total Active	VMS with MMSI	VMS match GFW	Fleet coverage
Longline	43	47	42	35	74%	49	44	36	71%
Purse seine	10	13	12	8	62%	13	10	10	77%
Supply vessel	6	7	7	5	71%	7	7	5	71%

Preprocessing and filtering of the data

For the subsequent analyses, only the VMS and logbook data with a matching MMSI to AIS data were used (**Figure 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. Therefore, the filtering process for VMS data removed between 36%-38% of longliner data and 39%-49% of purse seine data, and 26-39% for supply vessels. For AIS data, between 37%-41% of longline data, 87%-89% of purse seine data, and 81%-83% of supply vessel data were removed. The majority of the AIS data that were filtered from purse seine and supply vessel data were within 10 km around ports. Logbook data that did not have corresponding AIS data represented 30-38% of longline data and 27-28% of purse seine data.

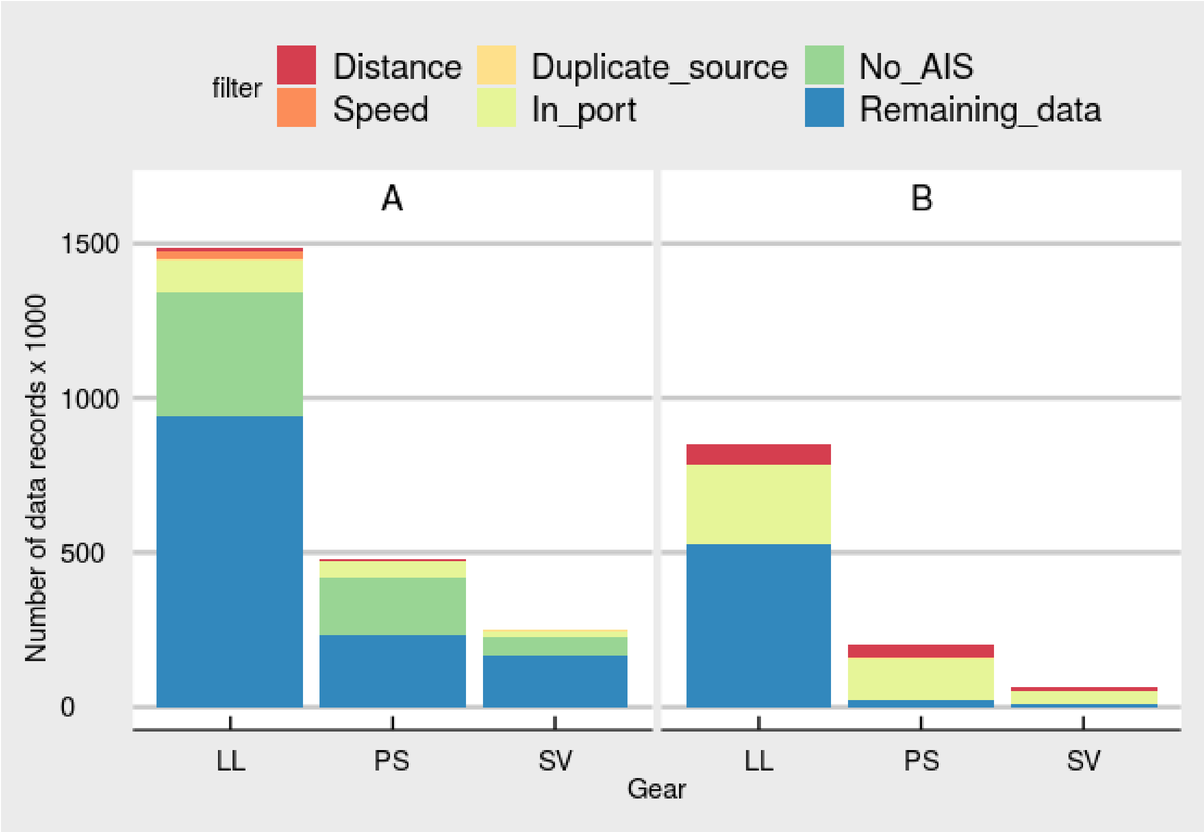

Figure 2 A) VMS and B) AIS data were filtered for distances < 5 m between transmissions, speed (> 13.5 knots for longliners (LL), > 18 knots for purse seiners (PS), and > 15 knots for supply vessels (SV)), duplicated timestamps due to transmissions received by different satellites or sources, and points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

Comparing transmissions

Of the Seychelles vessels using AIS, about 66% were using class B AIS and about 34% were using class A. 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](#)). Class B systems have lower transmission frequencies when there is a high density of vessels. 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 0.5° x 0.5° grid cell per month over 2016 and 2017 and for both gears for each data source. This grid resolution is a finer scale than that required by the Indian Ocean Tuna Commission (IOTC) at of 5°/month for longliners and 1°/month for purse seiners; thus any results will be more precise than reporting requirements.

Distance covered by vessels

In this chapter, we investigate the distance covered by each vessels as a measure of vessel activity (as opposed to fishing hours; REF TO PREVIOUS CHAPTER). Vessel positions of the filtered VMS and AIS data were interpolated into trajectories using a maximum time difference of 24 hours between subsequent points. We investigated the distance covered by each vessel by comparing the overall length of each trajectory for each vessel derived from either VMS (reference) or AIS data.

Spatial occupancy of fleet using aggregated trajectories

Vessel trajectories were overlaid on a 0.5° x 0.5° grid (**Figure 3**). The length of the trajectory within a grid cell was calculated and represents the distance covered by a vessel in that grid cell. Cumulated distance over vessels then represents the spatial occupancy of the fleet and can be used to describe the spatio-temporal patterns of occurrence. Gridded data were aggregated by month for each cell following current IOTC requirements for the temporal resolution of statistical fisheries data. Anomaly maps were created by subtracting the values of AIS from VMS for each cell.

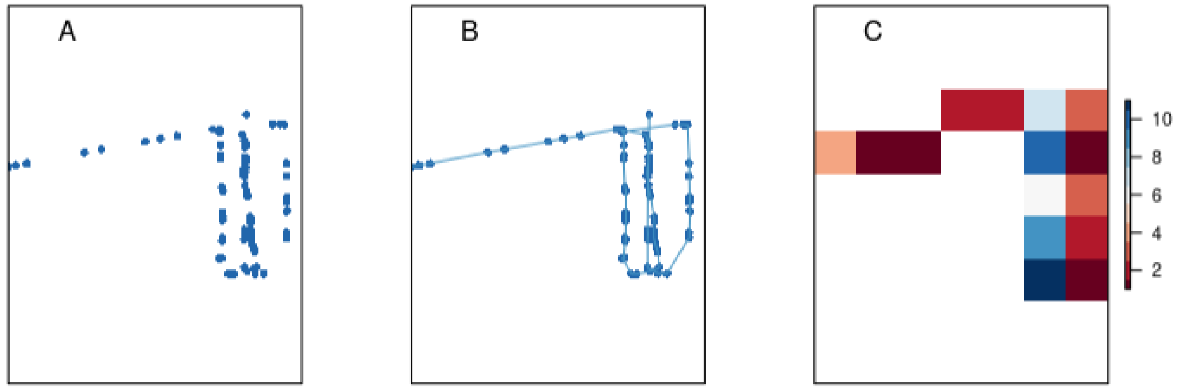

Figure 3 An example of the trajectory aggregation method using one month of VMS position data. A) Vessel positions given as latitudinal and longitudinal points are B) interpolated into trajectories and then C) overlaid on a grid. Data are then aggregated by averaging the distance of the vessel trajectory within each grid cell over a month.

Comparisons of GFW fishing predictions and logbook entries

The outputs from the GFW neural net algorithm to predict fishing activity were compared to the catches recorded in the official logbooks for the 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 a 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 events in each cell were summed over each period (2016 and 2017) for each gear and compared using linear regression.

Fishing effort from AIS

As a measure of effort for purse seine and support vessels, a buffer of 38 km was added around the trajectories and the surface area was then calculated, representing the surface area explored by vessels. This buffer covers the search zone of a vessel, i.e., the maximum radar range (20-25 nm) of detection of bird flocks generally associated with tunas (Assali et al. 2017).

As a measure of effort for longliners, we multiplied the number of fishing sets identified by the GFW neural net algorithm by the average number of hooks deployed for each fishing set during 2016-2017. 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 3670 (± 540) hooks to target swordfish and the tropical fishing grounds where they used on average 3000 (± 280) hooks to target bigeye and yellowfin during 2016-2017. GFW effort was then compared to logbook effort using 5° x 5° grid cells, in line with IOTC reporting guidelines.

Results and Discussion

Fleet coverage

Fifty-one longline vessels, 13 purse seine vessels and seven supply vessels are listed as active (i.e. have VMS data) in the Seychelles official registry for 2016 and 2017 (Table 1). Forty-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 coverage for 2016 is 74% of the 47 vessels active in the longline fishery, and 71% of the 51 active in 2017. Ten MMSI were found by GFW for the 13 Seychelles purse seiners. Eight of these MMSI could be matched to vessels active in 2016 (62% fleet coverage), and 10 could be matched to vessels active in 2017 (77% fleet coverage). Six MMSI were found by GFW for the seven Seychelles supply vessels that had VMS data, of which five were matched each year, indicating 71% fleet coverage.

Transmission frequency

We found that the transmission frequency of VMS data indicates that the Seychelles deep water tuna fishing fleet largely complies with the standard of one transmission per hour, with the predominant peak in transmission frequency at 60 minutes (**Figure 4A**). 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.

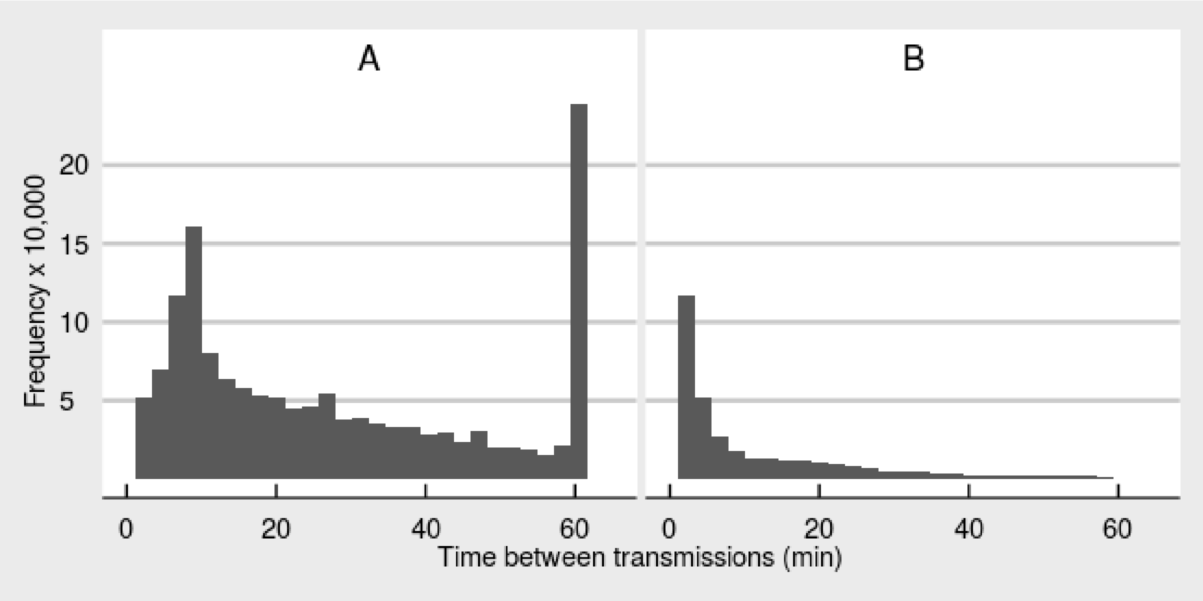

Figure 4 The frequency of transmissions for A) VMS and B) AIS data for all years and gear combined. Each plot represents the 90th percentile of each dataset. VMS transmissions have two peaks in frequency at 60 and 10 minutes (median = 22 minutes). The peak in AIS transmission frequency is about 3 minutes (median = 3.1 minutes).

Vessels with AIS were found to transmit their position about every 3 minutes (median = 3.1 minutes; [Figure 4B](#)). We find considerably more VMS than AIS transmissions across space and time ([Figure 2](#); [Figure 5](#)). The overall spatial trend between VMS and AIS transmissions is similar, but AIS have far fewer transmissions, especially in the western Indian Ocean ([Figure 5](#)). However, we find more transmissions from AIS than VMS offshore of southern Africa and around the Seychelles, perhaps be due to better coastal receiver coverage in these areas. Terrestrial coastal receivers receive messages between 10 to 50 nautical miles offshore.

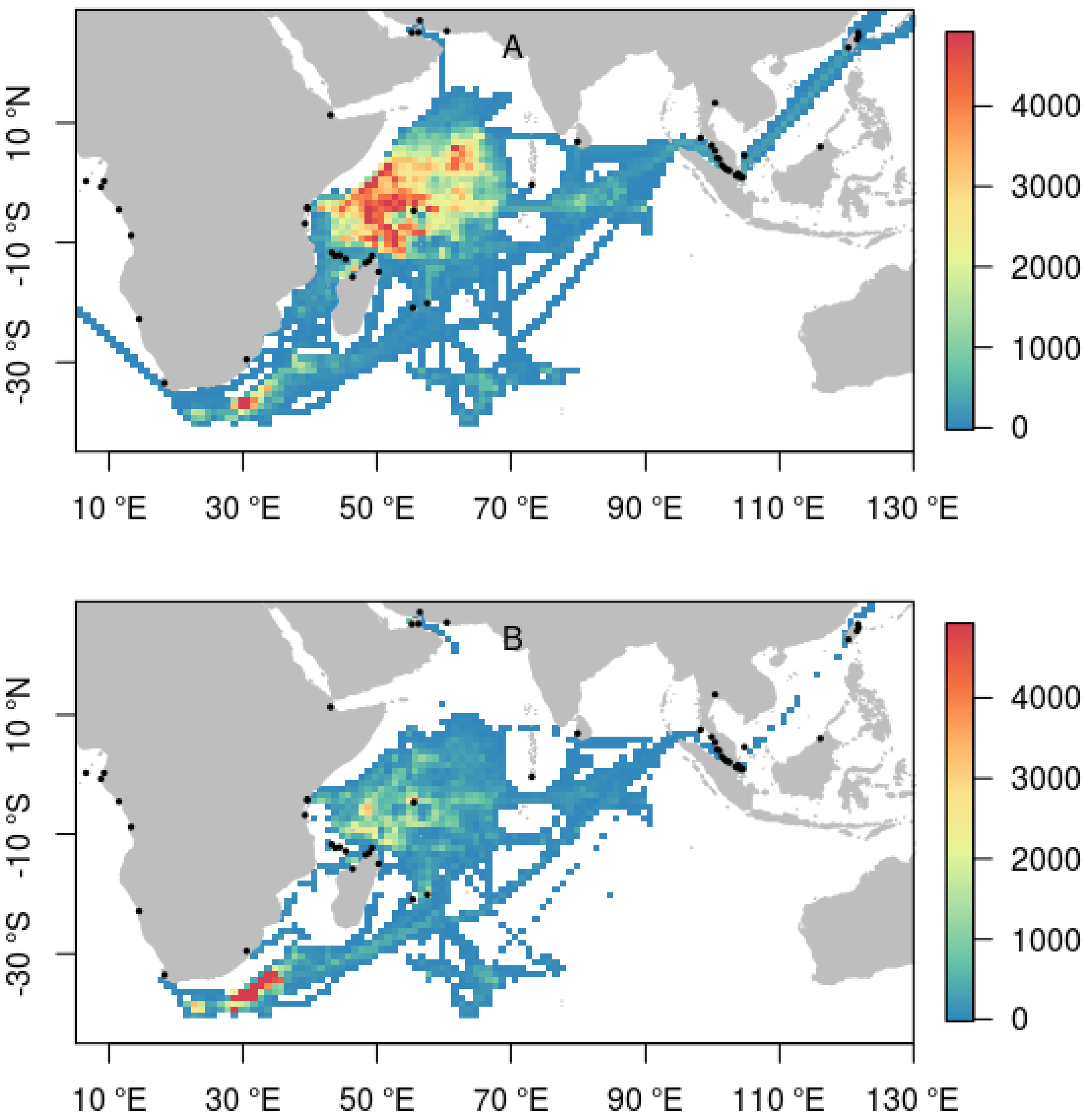

Figure 5 The number of transmissions per 1° x 1° grid cell for A) VMS and B) AIS data for both years and gears combined. Black points represent the ports identified in the study.

Spatial coverage using aggregated trajectories

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 seine vessels. AIS for longliners indicate that there is good coverage in the tuna fishing grounds in the western Indian Ocean (Figure 6A,B). In general, AIS is lacking on the extremities or the long trajectories made by one or few vessels.

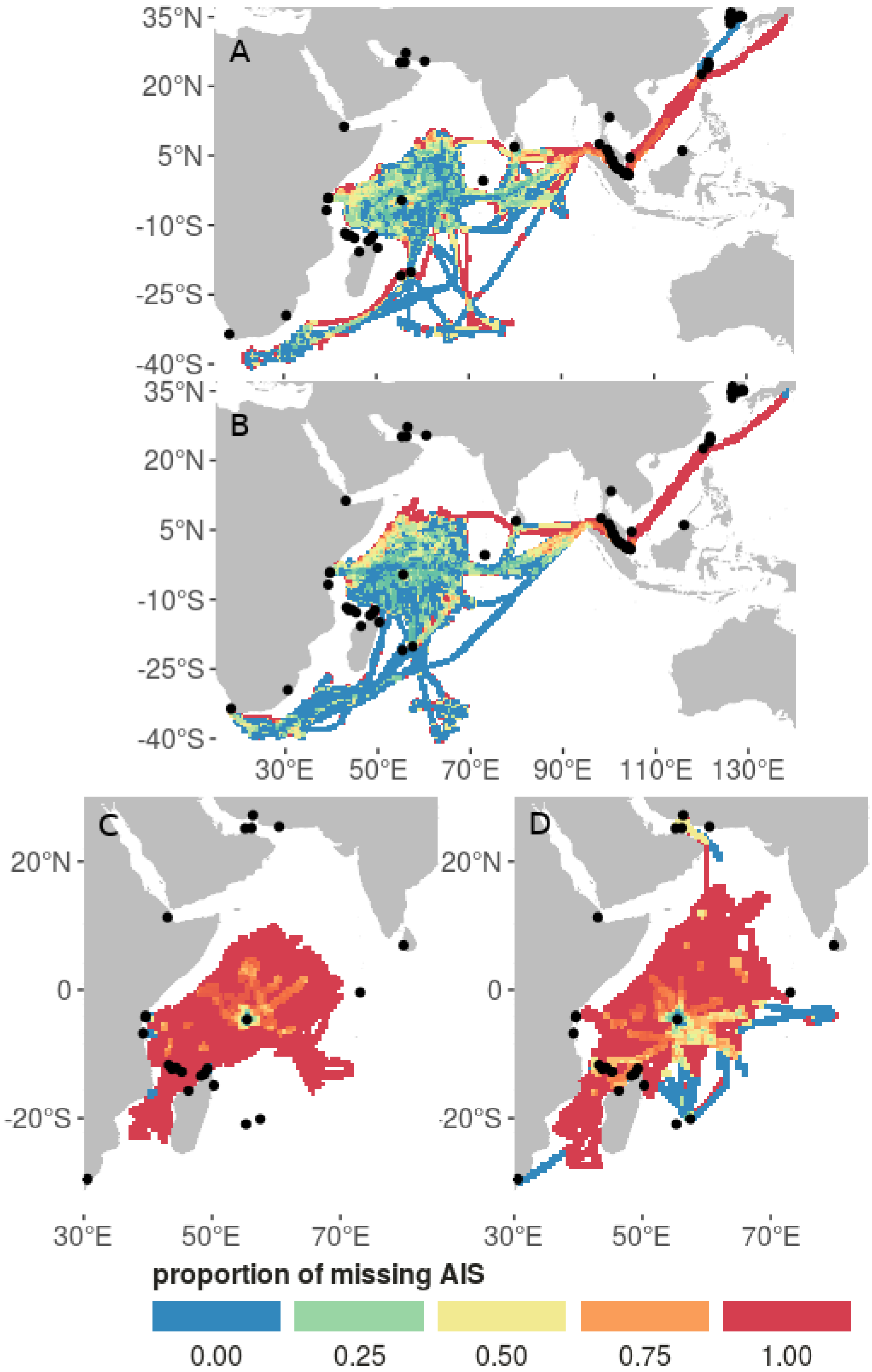

Figure 6 Spatial coverage of AIS data for longline vessels in A) 2016 and B) 2017, and purse seine vessels in C) 2016 and D) 2017. The color spectrum indicates the proportion of the time when the cell had data (AIS or VMS) and AIS data were available. Cells towards the red end of the spectrum indicate that no AIS data were available (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 purse seine 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 6C,D**), though there are more AIS reports in 2017 in the south east (**Figure 6D**).

AIS switch-off

For both longline and purse seine vessels, we found that spatial coverage increased gradually over the two years of data (**Figure 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; REF to Satellite and terrestrial coverage section.). Our findings indicate that there is a high likelihood of considerable AIS switch off, particularly for the purse seine fleet and their supply vessels. AIS transmissions are consistently and substantially lower in quantity than VMS data (**Figures 1,4,5,6,7**), even though the frequency of transmissions are much higher (**Figure 3**). This is evident for both longline and purse seine fleets, 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 western Indian Ocean (e.g. Atalanta). Though piracy was less of a concern during the study period than previously, this switch-off behaviour appears to continue for the purse seine fleet as part of the standard measures put in place by onboard private security companies.

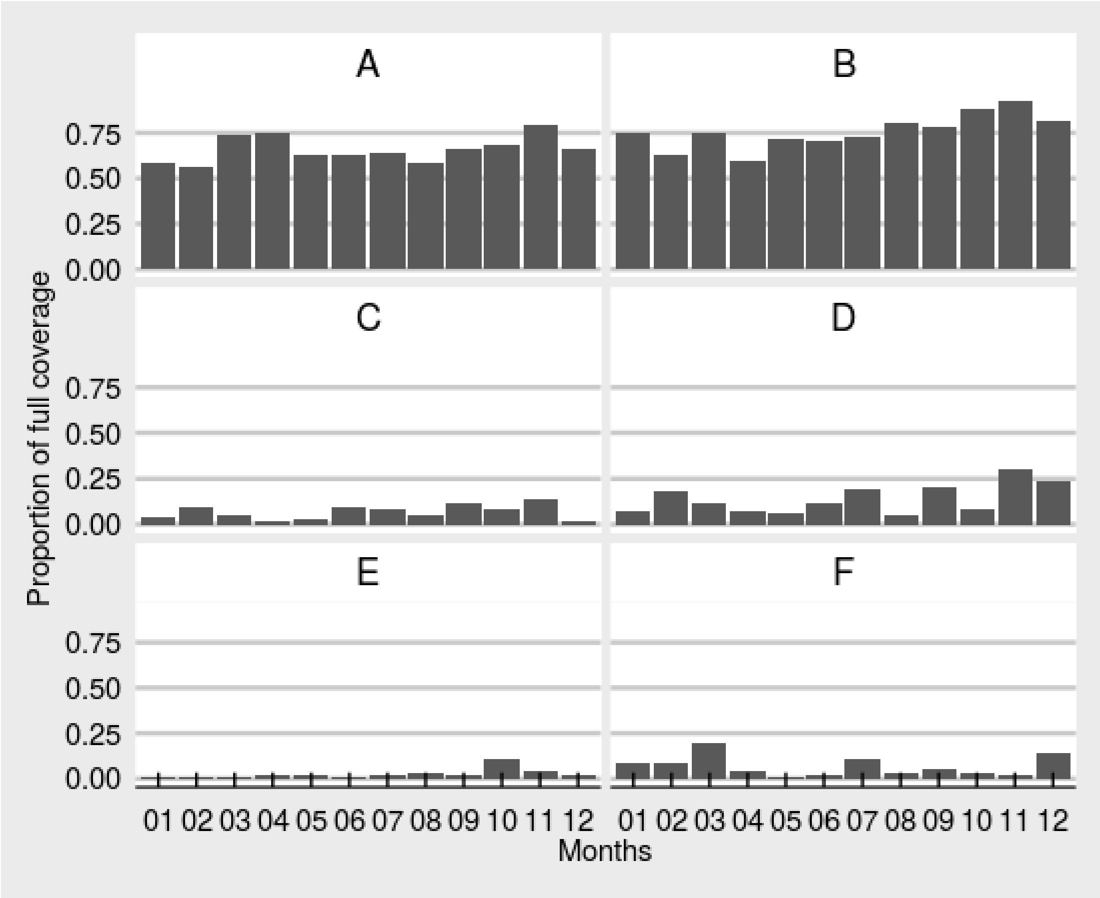

Figure 7 The monthly proportion of AIS spatial coverage relative to the full spatial coverage of AIS and VMS data combined for longliners in A) 2016 and B) 2017, purse seiners in C) 2016 and D) 2017, and supply vessels in E) 2016 and F) 2017.

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 8**; see Appendix I for monthly maps). The spatial pattern is very similar, indicating that vessels spend the majority of their time in the northwestern Indian Ocean. AIS generally show lower magnitude values than VMS data for the distance covered by vessels. This is due to the fact that VMS data have fewer and longer trajectories because they continuously record data and have few pauses between transmissions of > 24 hours. Whereas AIS data have many but short trajectories, as there are frequent breaks in transmission > 24 hours (e.g. **Figure 9**).

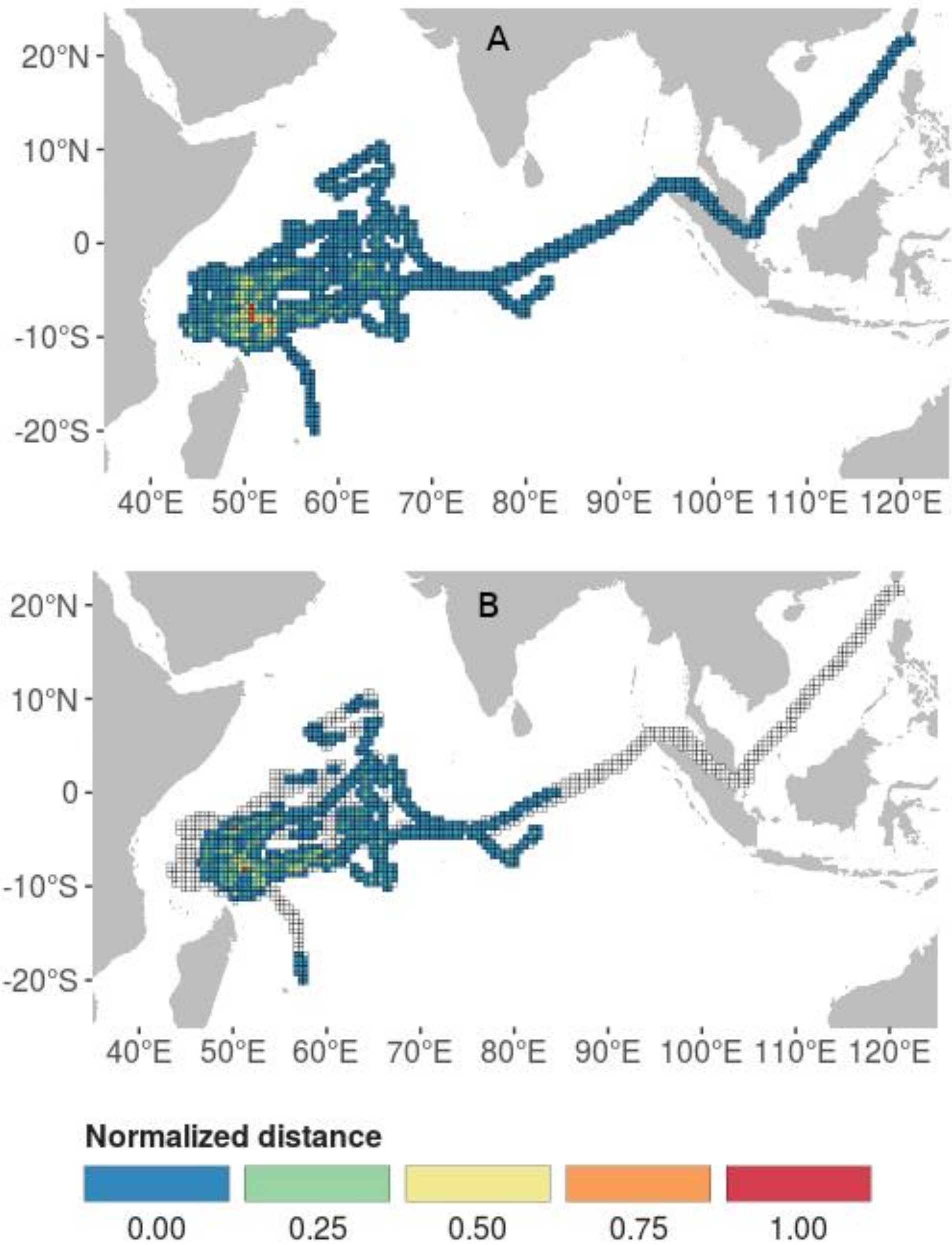

Figure 8 The normalized distance covered by Seychelles longline vessels in January 2016 as calculated by the length of the vessel trajectories within each cell aggregated over the month for A) AIS and B) VMS data. Higher values indicate that more distance was covered in a cell. White squares indicate missing data.

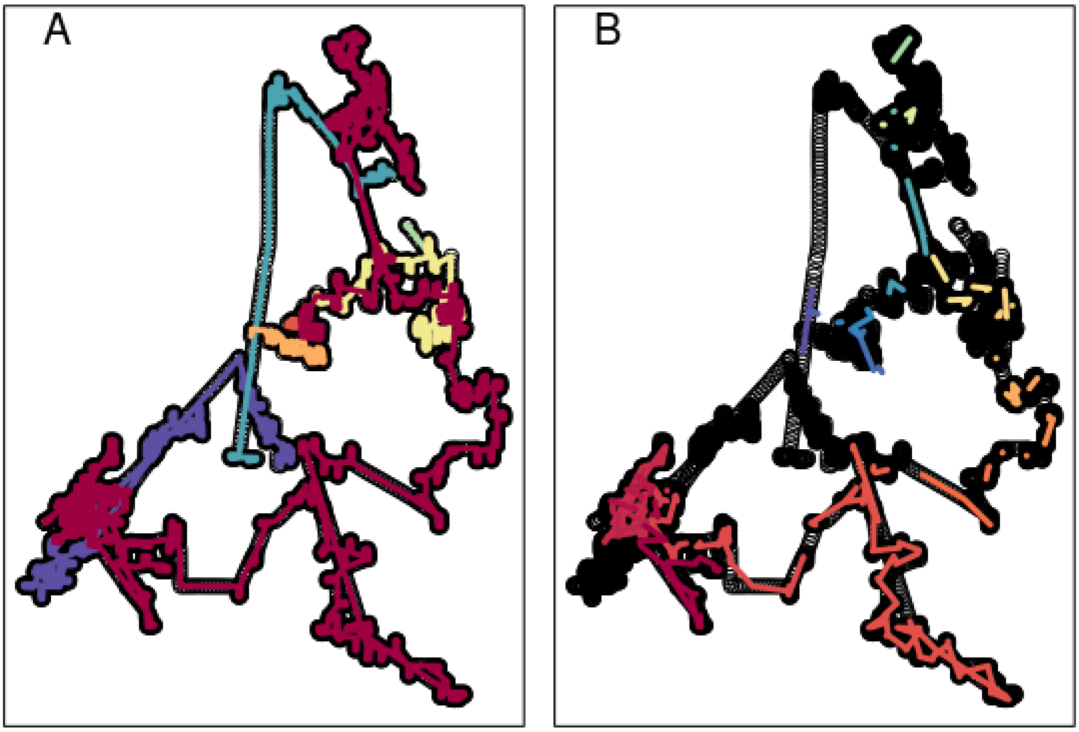

Figure 9: An example of trajectories calculated from longline A) VMS data (N trajectories = 7) and B) AIS data (N trajectories = 65). Black points on both plots are VMS transmissions. The different colored lines overlaid on the points represent different overlaid trajectories.

Surface area explored by purse seine vessels

The surface area explored by purse seine 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 the Seychelles, in line with the known fishing grounds of the purse seine fleet (e.g., **Figure 10A**; see Appendix I for monthly maps). As there are very few AIS data for purse seine vessels outside of port, the surface area explored by purse seiners using AIS data gives little useful information (e.g., **Figure 10B**; see Appendix I for monthly maps).

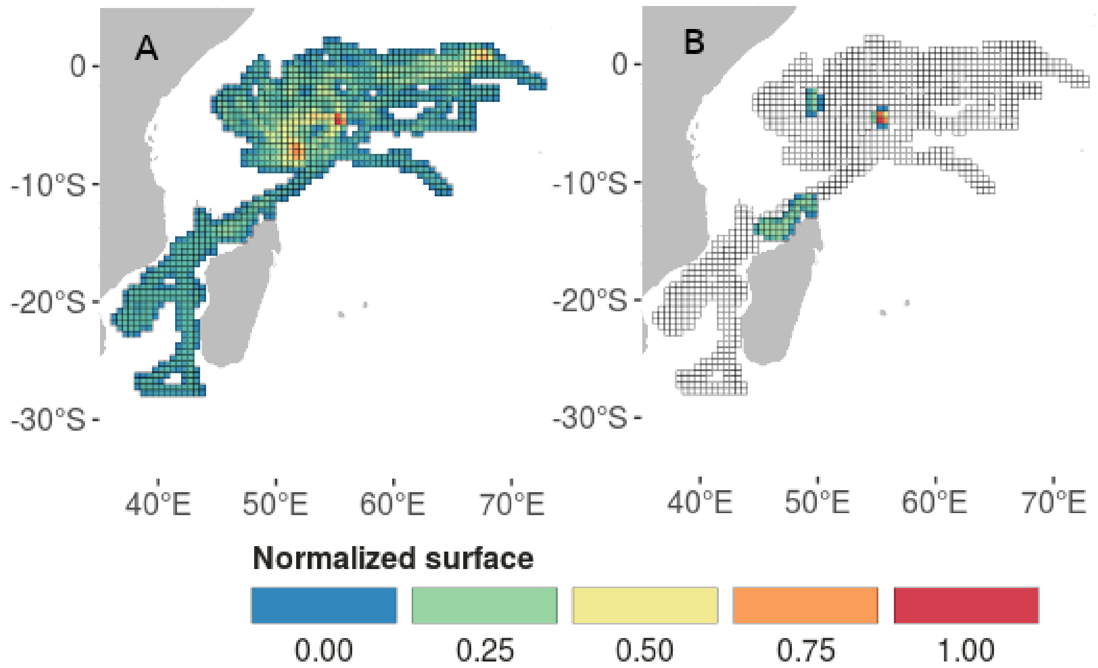

Figure 10 The normalized surface explored by Seychelles purse seine vessels in May 2017 as calculated by determining the surface area from the length of the vessel trajectories with a buffer of 38 km around the trajectory. Surface area is aggregated over the month for each cell for A) AIS and B) VMS data. Higher values indicate that more surface area was explored in a cell.

Accuracy of GFW fishing predictions compared to logbook data

We find that the GFW neural net algorithm is able to predict fishing activity relative to logbook data (i.e., true positive) for the longline vessels between 52% of the time in 2016 to 68% of the time in 2017, and has very low prediction rates for the purse seine vessels (**Table 2**). True negatives, where GFW predicts no fishing and there were no entries in the logbook, occurred 95.8% (2016) and 96.1% (2017) of the time. False positives, where GFW predicted fishing but the logbooks have no entry, were found 4.2% of the time in 2016 and 3.9% of the time in 2017. False negatives, where GFW did not predict fishing, but logbooks indicate catch, were found 7.5% (2016) and 35% (2017) of the time. In general, we find that fishing predictions are higher in 2017 than in 2016, including both true and false positive predictions, coinciding with better satellite coverage.

There are few AIS data for purse seines 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 predicts 'No fishing' for most of these data points, and predicts true positives <2% of the time in both 2016 and 2017 (**Table 2**).

Table 2 The accuracy of the predictions of fishing activity by the neural net algorithm provided by GFW for the longline (LL) and purse seine (PS) 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.

LL 2016, N=6927		AIS GFW algorithm		**PS 2016,N=2374**		AIS GFW algorithm	
		Fishing	No fishing			Fishing	No fishing
Logbook	Fishing	52.0%	7.5%	Logbook	Fishing	0.7%	0.4%
	No fishing	4.2%	95.8%		No fishing	2.9%	97.1%
LL 2017, N=5010		Fishing	No fishing	**PS 2017,N=2623**		Fishing	No fishing
Logbook	Fishing	68.0%	35.0%	Logbook	Fishing	1.5%	1.0%
	No fishing	3.9%	96.1%		No fishing	3.0%	97.0%

The spatial patterns of the positions where the neural net algorithm indicated fishing and the positions recorded in the logbook are very similar for longline vessels (Figure 11A,B). Looking at the percent difference between logbook and GFW predictions (i.e., ($Sets_{logbook}$-$Sets_{gfw}$)/$Sets_{logbook}$, Figure 11C,D), we find that GFW neural net predictions show many good predictions (differences near 0), with about 50% of the points underpredicted by GFW (differences greater than 0). The linear regression of logbook data versus neural net predictions indicates a good relationship for both 2016 (r^2 = 0.69) and 2017 (r^2 = 0.88), though it is worth noting that the coefficient of determination is biased due to the spatial autocorrelation of the data. We find, however, that the neural net algorithm consistently underestimates the logbook data by about half in 2016 (slope of the linear model = 0.52), and about 15% in 2017 (slope of the linear model = 0.85). Consistent with Table 1, we find better predictions in 2017 than 2016 (Figure 11C,D,E,F). No meaningful comparison is possible between the GFW algorithm and logbook entries for purse seine vessels as there are not enough AIS positions for purse seines in the fishing grounds.

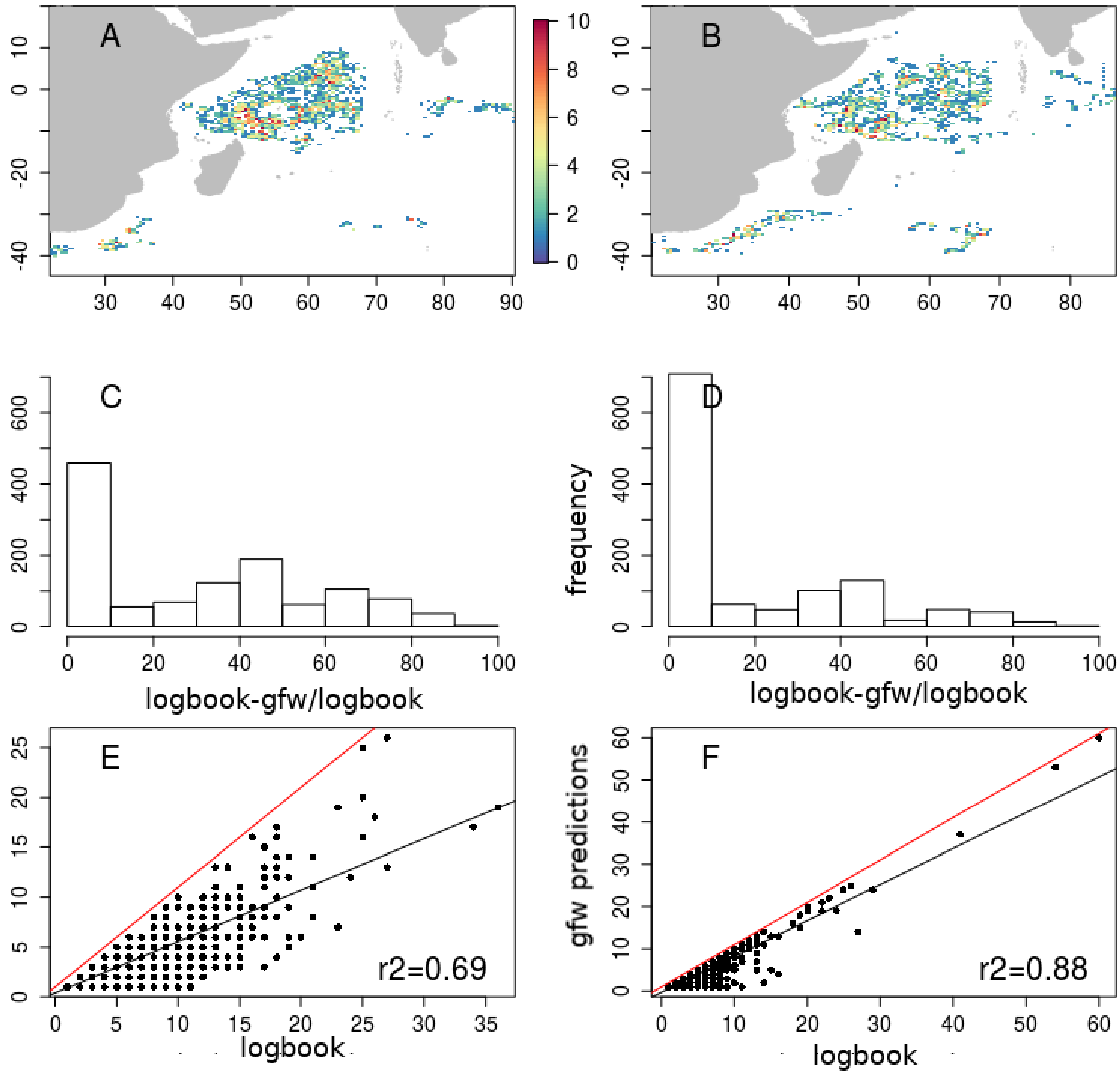

Figure 11: Positions where the GFW neural net algorithm predicts fishing events to occur for longline vessels in A) 2016 and B) 2017 on a 0.5° x 0.5° grid with fishing events summed over the period within each cell; the percent anomaly between coincident logbook data and the GFW predictions ($Sets_{logbook}$-$Sets_{gfw}$)/$Sets_{logbook}$) for C) 2016 and D) 2017, and linear regressions of the relationship between logbooks and GFW predictions for E) 2016 and F) 2017.

When comparing the true positive positions (i.e., not those aggregated on a grid) where the neural net algorithm predicts fishing on the same day as the logbook has a record, we find that the distances between the AIS positions and the logbook positions are relatively close for longliners, i.e., 75% of the AIS points are within 50 km of the logbook positions (Figure 12A,B). 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.

Purse seines set their nets over a distance of about 50 m. We find that 75% of the AIS points for true positive GFW neural net predictions are within 200 km of the logbook positions (Figure 12C,D), a spatial range far greater than that of a purse seine set, indicating that the scale of the spatial distribution of these true positives predictions does not well represent the positions recorded in the logbook.

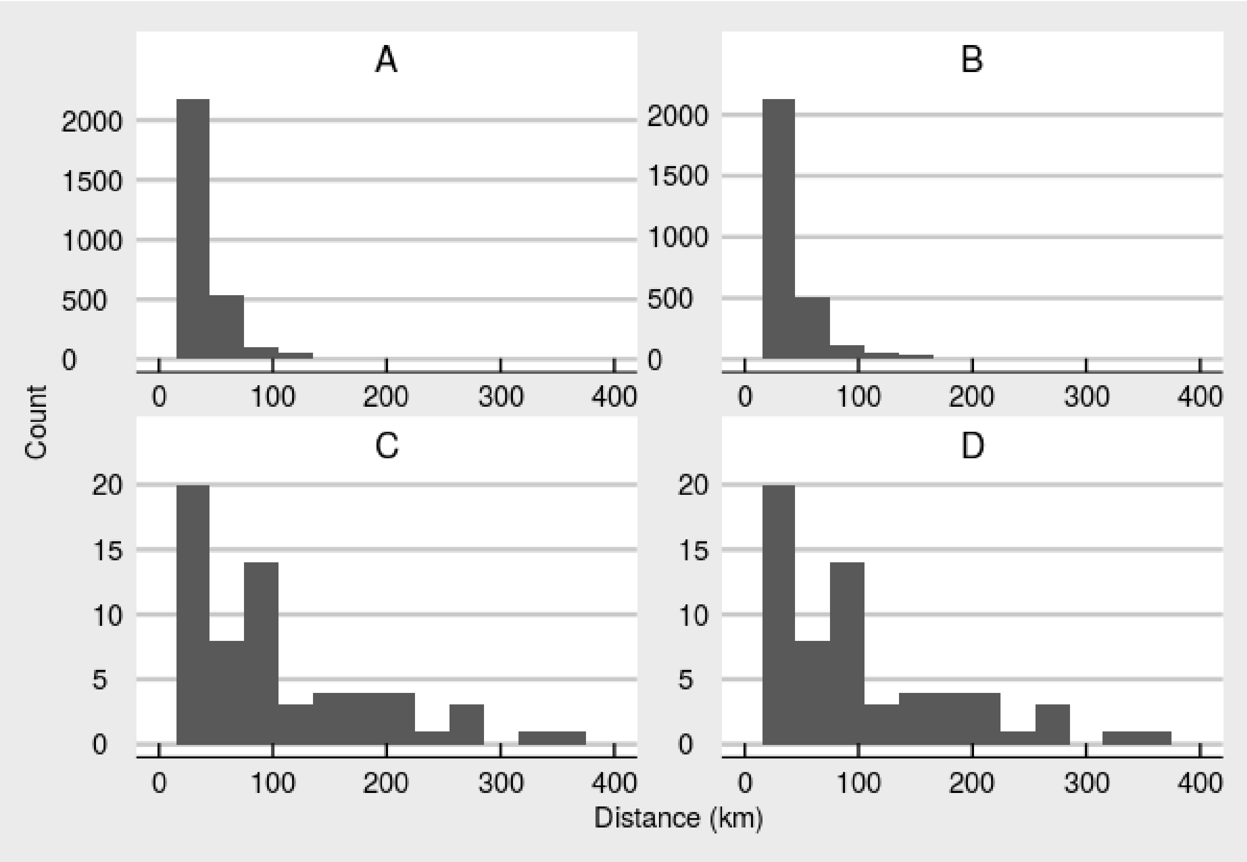

Figure 12 Distance (km) between logbook positions and AIS true positive fishing positions as predicted by the GFW neural net algorithm for longliners in A) 2016 and B) 2017 and purse seiners in C) 2016 and D) 2017.

We investigated the hour of the day in which the GFW neural net algorithm predicted fishing activity (all predictions, not limited to true positives), and found that for longline fishing, the predictions were reasonable (**Figure 14A,B**). 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 swordfish are set at night and are hauled in the morning and longlines targeting tuna are generally set during the day and hauled in the evening. However, the hours during which fishing is predicted for purse seiners are less likely. 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 activity during hours of darkness, i.e. 20:00 to 04:00 (**Figure 14C,D**).

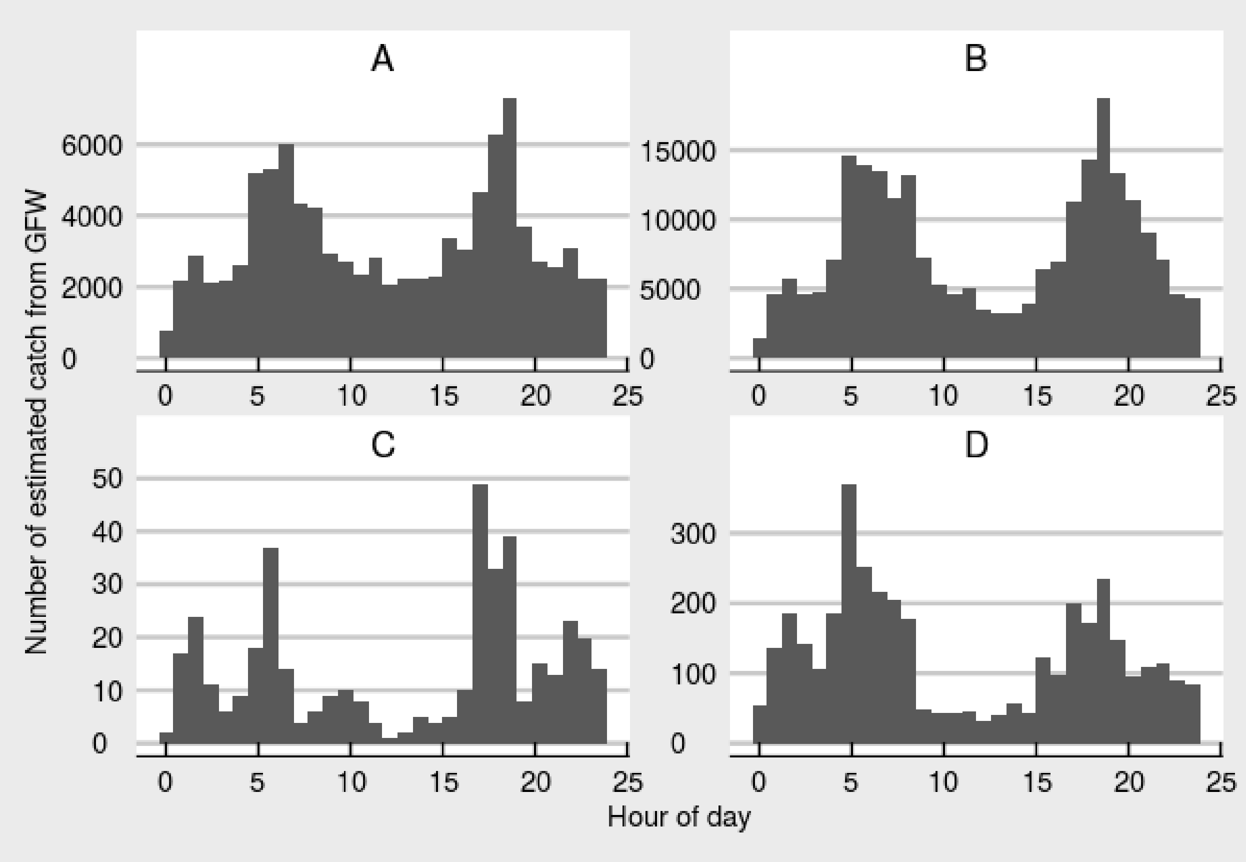

Figure 14 Hour of the day in which the GFW neural net algorithm identifies fishing for longline (LL) vessels in A) 2016 and B) 2017 and purse seine (PS) vessels in C) 2016 and D) 2017.

Longline fishing effort

We find that estimations of effort using GFW neural net predictions of fishing sets have a strong linear relationship with effort as reported by the number of hooks in the logbooks for both 2016 (r^2 = 0.91) and 2017 (r^2 = 0.95) (Figure 15). As with GFW predictions of fishing events, effort calculated using GFW predictions consistently underestimates the actual effort reported by logbooks by about 50% (slope of the linear model = .51) in 2016 and by about 27% (slope of the linear model = 0.73) in 2017.

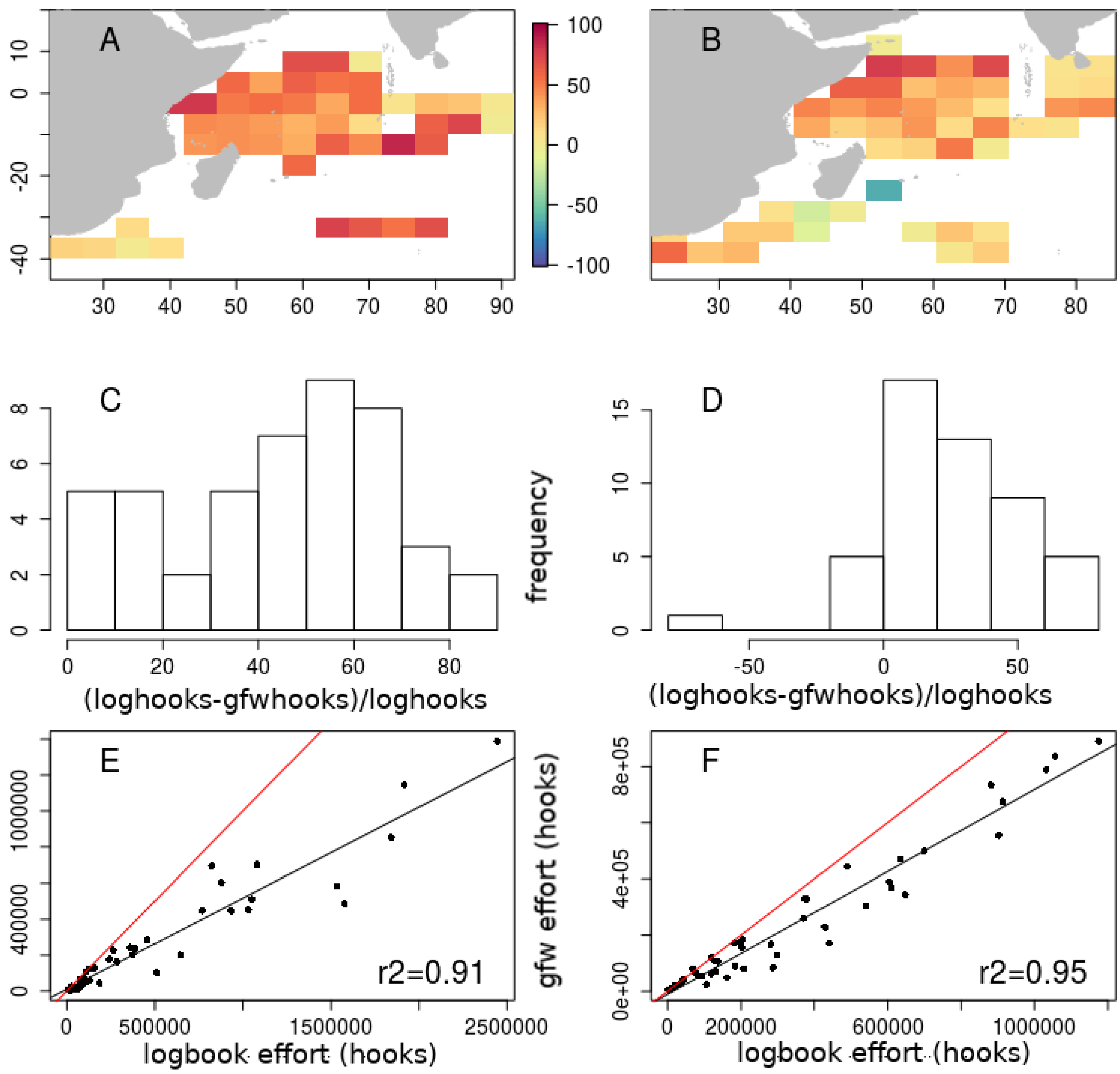

Figure 15: Normalised anomaly maps of longline fishing effort (hooks) calculated as the number of logbook hooks minus the number of GFW hooks on a 5° x 5° grid, normalised by the number of logbook hooks for A) 2016 and B) 2017; the distribution of the normalised anomaly of fishing effort between logbooks and GFW for C) 2016 and D) 2017, and the linear relationship between logbook effort and GFW effort for E) 2016 and F) 2017.

Conclusions

In general, we find that AIS have good data coverage in terms of the AIS equipment on board the Seychelles fleet, covering between 50% (longliners) to 70% (purse seiners) of the vessels. The transmission frequency of AIS (about 2 minutes) is significantly more frequent than that of VMS (< 1 hour). The spatial coverage of the AIS data are good for longline vessels, with good coverage over the fishing grounds, and only the extremities and long trajectories missing. However, AIS data are deficient for purse seine vessels, with data only present around ports, and almost none found in the fishing grounds. Consistent with this spatial data coverage, we find that the GFW neural net algorithm predicts well the fishing activity for longliners (up to 68% of true positives), but predictions for purse seiners are not informative. As well, we find that metrics for effort are very similar when calculated using logbooks or GFW predictions for longliners, but are not comparable for purse seiners. We find that at the reporting resolutions required by the IOTC (i.e., 5°/month for long line vessels for both catch and effort), AIS performs well. We also find that improvements in AIS data coverage and GFW fishing predictions occur between 2016 and 2017, possibly in connection to improved satellite coverage. While this should lead to improved predictions, it also means that data are inconsistent over time, and cannot be used with confidence in, for example, CPUE time series.

Perspectives, issues and caveats of using AIS for fisheries monitoring

A major issue that we have identified with the use of AIS data for fisheries monitoring of the purse seine fleet is the low spatial coverage and switch-off behaviour, which make these data unusable for subsequent analysis. AIS data are much more useful for the long line fleet; though the frequent breaks in transmission for long line vessels lead to consistent underprediction by AIS and GFW algorithms of the "true" patterns shown using VMS and logbook data. However, as we have shown through our analysis, this bias can be accounted for using linear models.

It is clear that AIS cannot be used for fleet-specific indices of effort, which require a much higher level of detailed data. However, our study indicates that GFW predictions can be a good indicator of the spatial and temporal trends of fishing activity for data-poor fleets. These predictions can be useful in identifying fishing grounds where spatial data are missing, and at the spatial-temporal resolution of IOTC reporting requirements, GFW predictions can be a good indicator of effort expended (e.g., hooks deployed).

Currently, there are no mandates that require AIS transmissions. Use of AIS for purposes other than near-port safety require the cooperation of users.

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References

Assan C, Lucas J, Augustin E, de Molina D, Maufroy A, Chassot E (2015) Seychelles auxiliary vessels in support of purse seine fishing in the Indian Ocean during 2005-2014: Summary of a decade of monitoring. IOTC–2015–WPTT17–41 Rev_1. http://iotc.org/sites/default/files/documents/2015/10/IOTC-2015-WPTT17-12_-_EU_PS_statistics.pdf

Assali C, Bez N, Tremblay Y (2017) Seabird distribution patterns observed with fishing vessel’s radar reveal previously undescribed sub-meso-scale clusters. *Scientific Reports*. 7:7364.

Bez N, Walker E, Gaertner D, Rivoirard J, Gaspar P, Walters C. Fishing activity of tuna purse seiners estimated from vessel monitoring system (VMS) data. Canadian Journal of Fisheries and Aquatic Sciences. 2011; 68: 1998–2010. doi: 10.1139/f2011-114

Chassot E, Dewals P, Floch L, Lucas V, Morales-Vargas M, Kaplan D (2010) Analysis of the effects of Somali piracy on the European tuna purse seine fisheries of the Indian Ocean. IOTC-2010-SC-09. http://iotc.org/sites/default/files/documents/proceedings/2010/sc/IOTC-2010-SC-09.pdf

Kroodsma, D. A., Mayorga, J., Hochberg, T., Miller, N. A., Boerder, K., Ferretti, F., ... &
Woods, P. (2018). Tracking the global footprint of fisheries. Science, 359(6378),
904-908.

Lee J, Andy BS, Jennings S (2010) Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. ICES Journal of Marine Science, 67(1), 1260–1271,https://doi.org/10.1093/icesjms/fsq010

Miller NA, Roan A, Hochberg T, Amos J, Kroodsma DA (2018), Identifying Global Patterns of Transshipment Behavior, *Frontiers in Marine Science*. DOI: 10.3389/fmars.2018.00240

Recommendation ITU-R M.1371-5 (02/2014) Technical characteristics for an automatic identification system using time division multiple access in the VHF maritime mobile frequency band. M Series Mobile, radiodetermination, amateur and related satellite services. http://www.itu.int/publ/R-REC/en

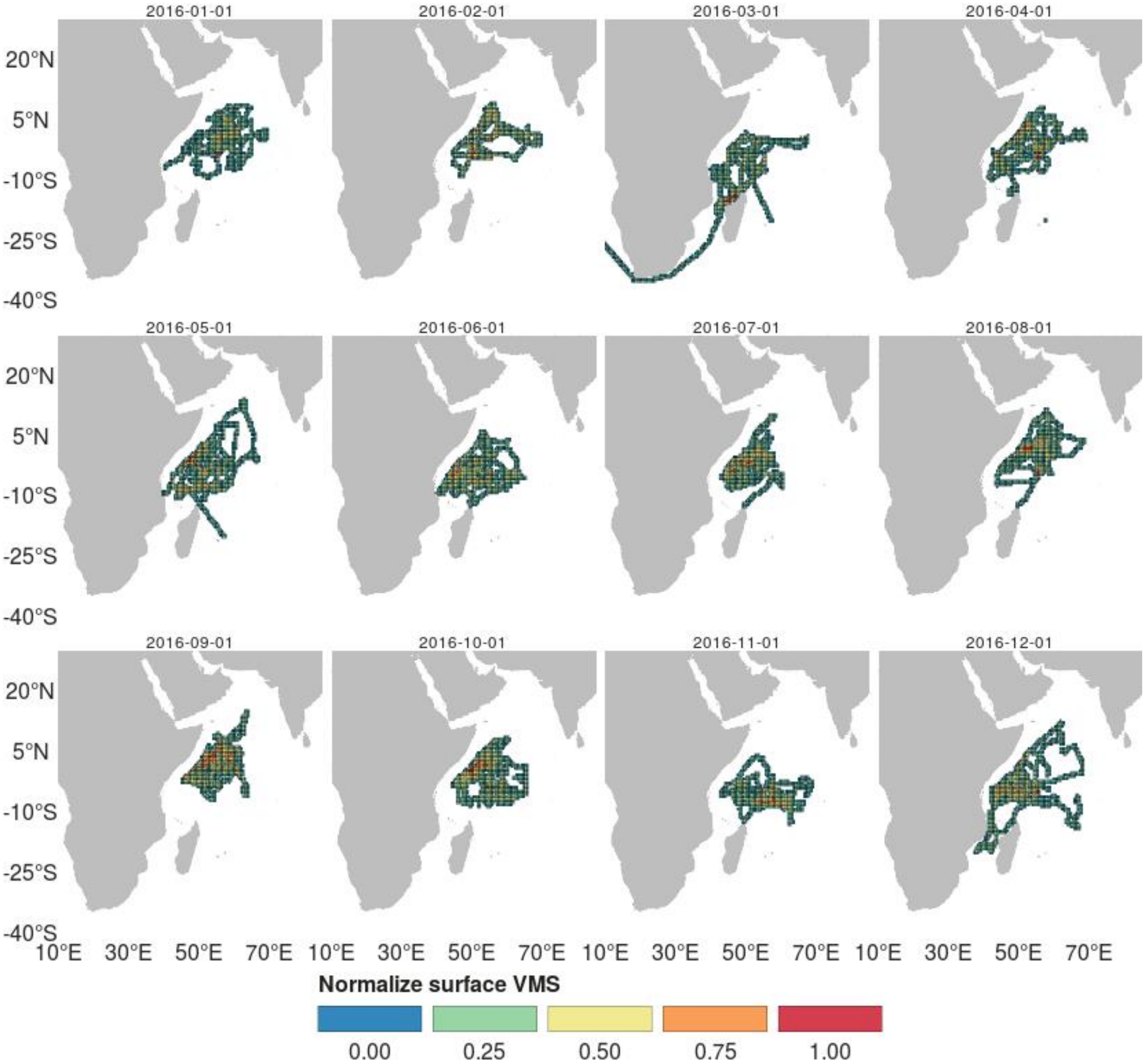
Robards MD, Silber GK, Adams JD, Arroyo J, Lorenzini D, Schwehr K, Amos J Conservation science and policy applications of the marine vessel Automatic Identification System (AIS)—a review. Bulletin of Marine Science. 92(1):75–103. 2016. http://dx.doi.org/10.5343/bms.2015.1034

Sala E, Mayorga J, Costello C, Kroodsma D, Palomares MLD, Pauly D, Sumaila UR, Zeller D (2018) The economics of fishing the high seas.Sala et al., Sci. Adv. 2018;4: eaat2504.

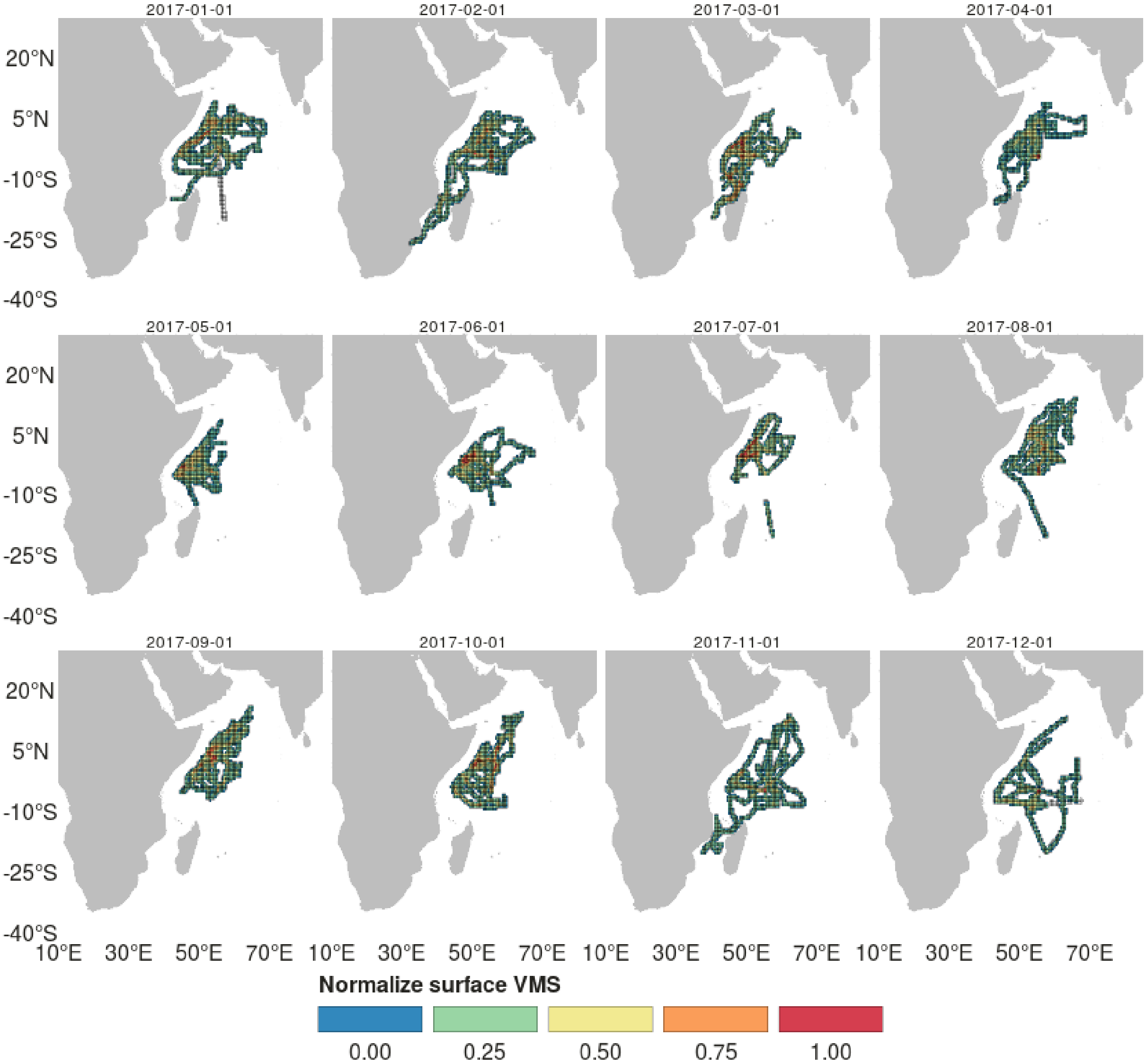
Witt JW, Godley BJ (2007) A Step Towards Seascape Scale Conservation: Using Vessel Monitoring Systems (VMS) to Map Fishing Activity. https://doi.org/10.1371/journal.pone.0001111

Appendix 2. Surface area explored

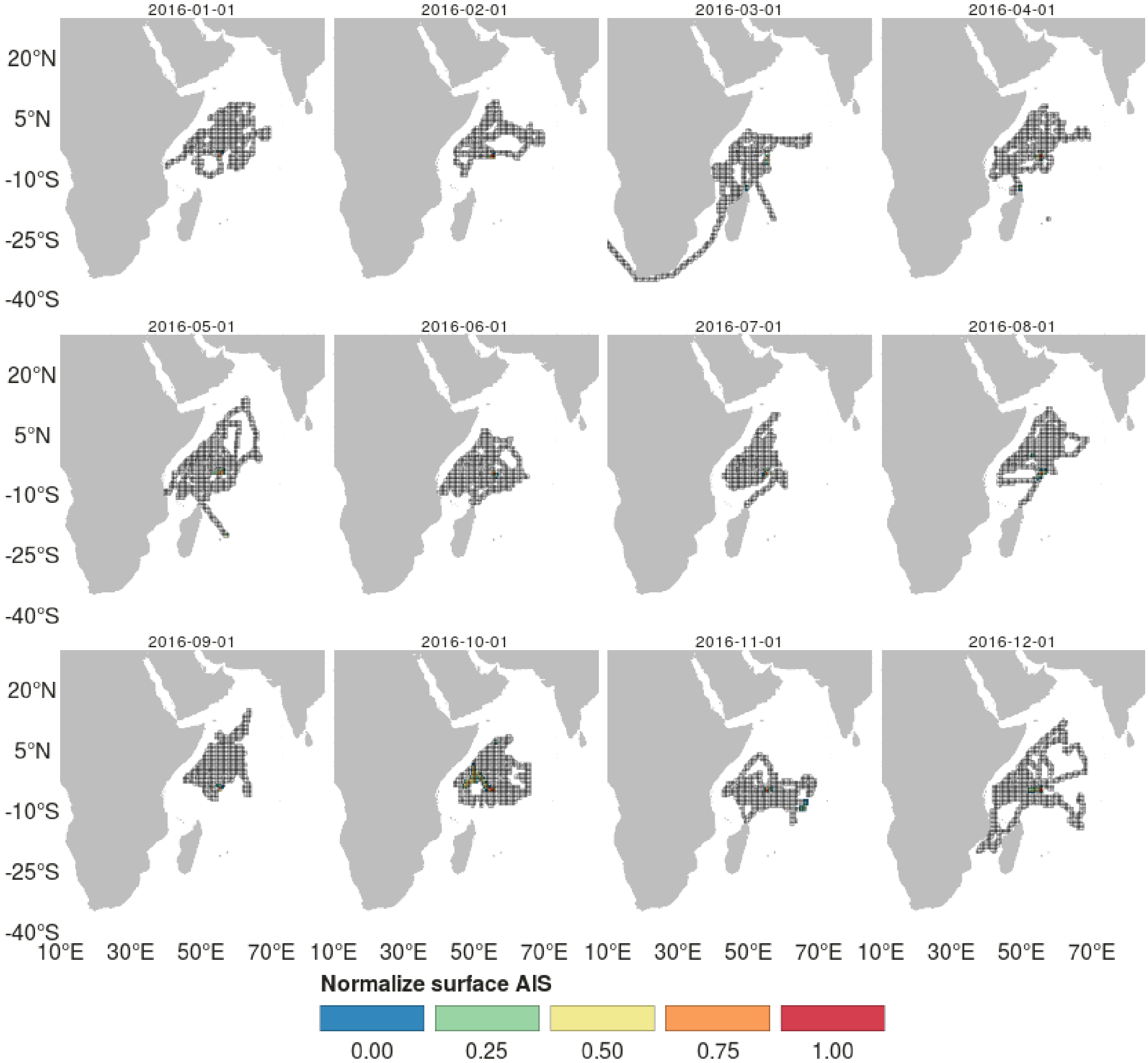
Appendix 2.1.1 The surface area explored by supply vessels for each month in 2016 calculated using VMS data.



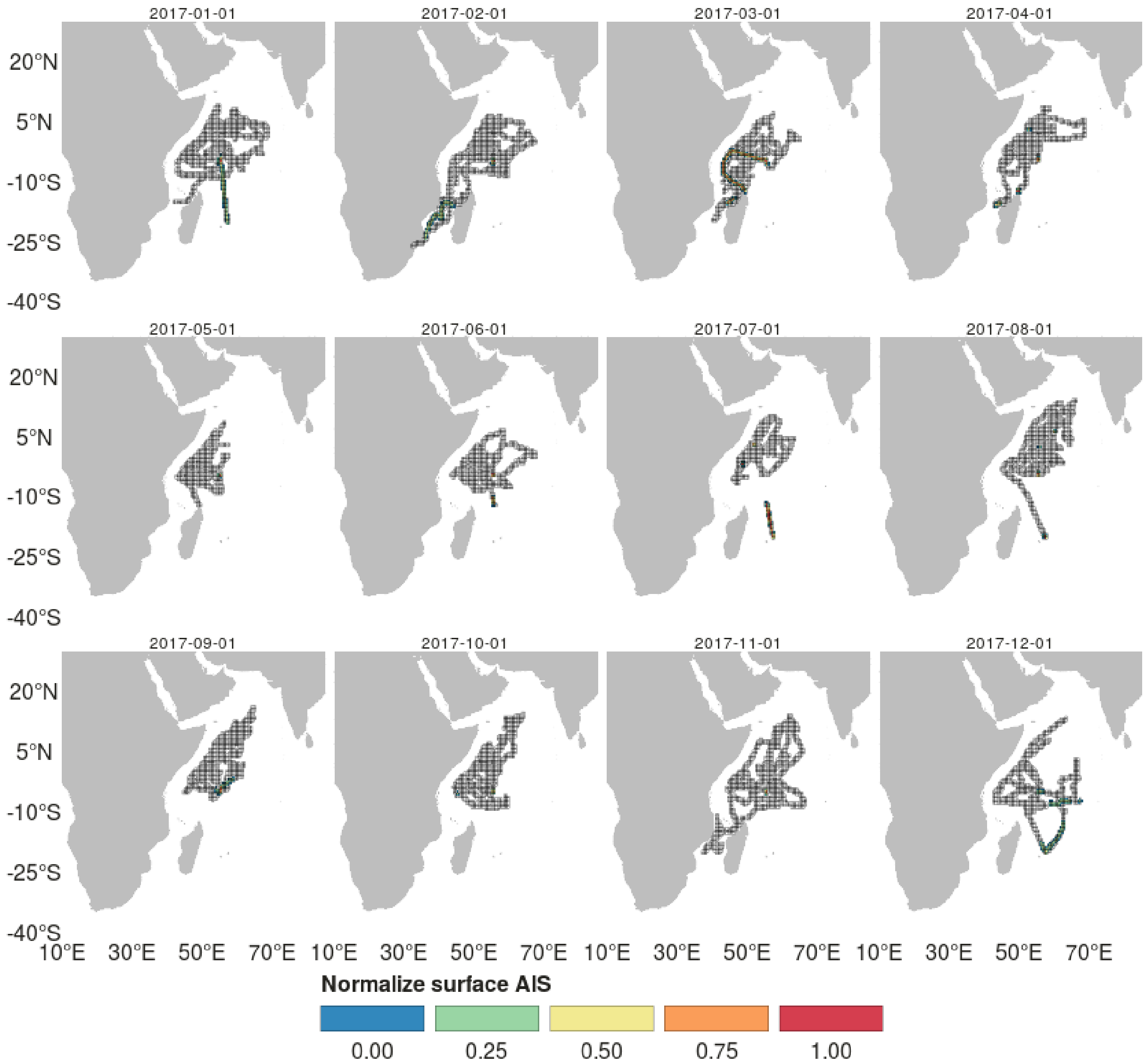
Appendix 2.1.2 The surface area explored by supply vessels for each month in 2017 calculated using VMS data.



Appendix 2.2.1 The surface explored by supply vessels for each month in 2016 calculated using AIS data.



Appendix 2.2.2 The surface explored by supply vessels for each month in 2017 calculated using AIS data.



Appendix 2

Figures of the surface area explore by long line, purse seine, and supply vessels for each month in 2016 and 2017