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Using anti-theft tracking devices to infer fishing vessel activity at sea

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ABSTRACT

Quantifying accurately human impacts on marine ecosystems is key to healthy oceans. While fish production from wild stocks has plateaued since the 1980 s, those estimates are primarily drawn from large-scale commercial fisheries, whose boats are routinely monitored using a suite of sophisticated equipment to ensure compliance. Smaller vessels, however, especially in developing countries, have not been so rigorously scrutinised due to their sheer number and the associated high surveillance cost. This study investigated the viability of using low-cost anti-theft devices to detect spatio-temporal patterns of fishing activity in the small- to medium-scale snapper fishery of Indonesia. SPOT Trace® GPS tracking units (SPOT, LLC) were deployed on a voluntary, participatory basis, on 130 deep water fishing boats ranging from 1.5 to 29 m in length. GPS data were subsequently analysed through a port identification and trip segmentation algorithm, before using spatial clustering to automatically identify positions likely associated with fishing events. Through this procedure, we identified a total of 2650 fishing trips, whose durations ranged from 4.3 h to 55.3 days. Fishing occurred primarily near vessels' home ports, but also offshore in the Jawa Timur province, and in the Timor and Arafura Sea near the Australian Economic Exclusion Zone (EEZ). Adopting this technology as a low-cost alternative to traditional VMS could greatly empower monitoring agencies through surveillance of a previously poorly documented stratum of the commercial fishing sector, and result in better long-term management of fish stocks and marine resources.

1. Introduction

1.1. Global state of fisheries and current issues

Nearly 10% of the world's population relies on the seafood industry as a source of income, with fish consumption constituting about 17% of the global intake of animal protein (FAO, 2020; Islam et al., 2014). The world's annual total fishery capture in 2018 reached a record high of 96.4 million tonnes, representing over US$150 billion (FAO, 2020). While fisheries are critical for food security and appropriate nutrition of the world's growing population, their economic future and viability are threatened with 34% of fish stocks currently overfished, 59.6% fully fished, and over 1100 threatened or near-threatened fish species on the IUCN Red List affected by over-exploitation (FAO, 2020; Maxwell et al., 2016). Illegal, unregulated and unreported (IUU) fishing is also a growing concern for the seafood industry as it is estimated at 26 million tonnes of fish annually, *i.e.* over 20% of global catch (FAO, 2016). While some actions such as the 2009 Agreement on Port State Measures to Prevent, Deter and Eliminate Illegal, Unreported and Unregulated Fishing have been implemented to combat illegal fishing, managing this economic and ecological threat remains challenging (FAO, 2020). This is partly due to the sheer number of vessels globally – estimated at 4.6 million in 2018 (FAO, 2020). These vessels use a myriad of ports and informal landing sites, with only a fraction of boats covered by surveillance operations through the systematic use of tracking devices.

1.2. State of Indonesian fisheries

Asia accounts for 85% of the global population engaged in the fisheries sector and 75% of the global fishing fleet, with Indonesia the

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second largest marine fish producer worldwide (FAO, 2020). Despite limited reliable catch data available, Indonesian fisheries are deemed fully exploited or over-exploited (Ministerial Decree No. 50/2017 on Estimation of MSY, Total Allowable Catch, and Exploitation Rate for fish resources in Indonesian Fisheries Management Areas), and lack effective harvest controls (Heazle and Butcher, 2007). Furthermore, the governments of Indonesia are facing high levels of illegal fishing, in particular from foreign fishing vessels (Resosudarmo et al., 2009; Wagey et al., 2009). For instance, industrial illegal fishing in the Indonesian Arafura Sea has been estimated to be substantial, approximating 1.5 times the area's legal catch and costing the government about US$2 billion in lost revenue (Resosudarmo et al., 2009; Varkey et al., 2010). Lastly, reported catch rates for the country (8% of global marine captures, representing 6.7 million tonnes in 2018) are likely underestimated, partly because of the predominance of small-scale fishing fleets and the large number of scattered landing sites (FAO, 2020). Indeed, while the livelihood of up to 90% of the capture fishery workforce depends on small-scale fisheries, getting accurate catch figures is notoriously difficult as boat registration is often not required nor reported in official statistics and those vessels' areas of operation are typically remote, as is the case for Indonesia's deep water snapper fishery (FAO (2020); Halim et al., (2020, 2019)).

1.3. Indonesia's deep water snapper fishery

Indonesia's deep water snapper fishery targets snappers *Lutjanidae*, groupers *Serranidae*, grunts *Haemulidae*, emperors *Lethrinidae*, croakers *Sciaenidae* and co-occurring species at depths ranging between 50 and 500 m (Amorim et al., 2020). There are over 100 species regularly caught in these fisheries, but the bulk of the catch is much less diverse with 60% of catch volume consisting of only 11 snapper species. The most common gears are drop lines and bottom-set longlines, and less common are baited traps and gillnets, set either deep or vertical along outer reef walls. The snapper fleet in Indonesia includes close to 11,000 fishing boats, representing a total annual catch in 2020 of around 120, 000 metric tons, with retail value amounting to about $US 1.2 billion (Mous et al., 2021). Fishing vessels range from powered canoes of less than 1 GT, which make day trips, to larger vessels measuring close to 100 GT and making trips of up to six months. Fishing grounds are spread out over the entire Indonesian archipelago but the most important ones in terms of volume are broadly distributed in the Indonesian part of the South China Sea, the Java Sea, and the Indonesian part of the Arafura Sea. An assessment of the global trade in snappers is hampered by lack in granularity in catch statistics (Cawthorn and Mariani, 2017), but Indonesia is the world's leading producer of snappers (FAO, 2020).

1.4. Understanding spatio-temporal patterns in fishing effort

A thorough understanding of fishing practices and catch composition is critical to implement efficient management policies, and several technologies are already available to estimate and monitor fishing effort at a fine scale remotely. Automatic Identification System (AIS) and Vessel Monitoring System (VMS) data may help identify vessels' fishing locations, anchorages and ports, along with trans-shipment events. VMS, in particular, is routinely used in many fisheries to monitor vessels in protected areas or to assess days at sea against fishing quotas (Chang and Yuan, 2014; Harrington et al., 2007; Maina et al., 2018; Marrs et al., 2002; Muench et al., 2017). Inferring fishing activity solely from vessel location recorded at given time intervals nonetheless remains an analytical challenge (Lee et al., 2010; Russo et al., 2014; Watson and Haynie, 2016). Such predictions require complex statistical models that account for several types of covariates (*e.g.* location-derived metrics, bathymetry, distance from shore, port identification) and are often further complicated by the crew's ability to turn transponders off (Muench and others, 2017; Peel and Good, 2011). Furthermore, VMS equipment and communications remain expensive (several thousands of $US) and thus not viable economically to be deployed on all fishing vessels. This is particularly problematic in developing countries for monitoring large small-scale fishery fleets and understanding how fishing is distributed spatially and temporally.

1.5. Objectives

Here, we report on the feasibility of mapping and quantifying accurately fishing effort for small fishing vessels operating in Indonesia's deep water snapper fishery from a low-cost VMS alternative that is typically used as personal asset tracking devices. Using this technology, our main objective was to discriminate and quantify vessel behaviour through an automated analytical framework and understand what factors may be driving the spatial distribution of fishing activity. Additionally, we investigated transponder shutdown events to gain insights into potential patterns of non-compliance.

2. Methods

2.1. Data collection

In 2014 The Nature Conservancy (TNC) initiated its opt-in Indonesia Fisheries Conservation Program by deploying SPOT Trace® GPS receivers (~$100 USD each, plus $140 USD annual subscription fees; Spot LLC, Covington, LA) on 130 small- to medium-scale fishing vessels, ranging from 1.5 to 29 m in length and between 1 and 81 in gross tonnage. SPOT Trace devices use the Globalstar satellite constellation and are designed to record GPS locations (median location error of ~8–10 m) only when detecting movement to save battery for long-term monitoring. On the water, where constant vibrations may cause false tracking events, SPOT Trace transmitters use their vibration sensor and compare consecutive GPS readings to determine if a boat is actually moving. When stationary for over five minutes, transmitters suspend their functions until activity is resumed, *i.e.* defined by showing two readings more than 200 m apart, and send a message advising that movement has momentarily stopped. GPS sampling nominal intervals may range from 2.5 to 60 min, the latter being the typical configuration used in this study (Lehrke et al., 2017).

All GPS locations are subsequently transmitted to communication satellites before being relayed to ground stations for processing, storage, and online publication. To provide long-term archiving of SPOT Trace data, catch composition and operational details of fishing trips, TNC developed I-Fish, a private database information system that can be queried by boat captains, boat owners, and policy makers to improve Indonesian fishery management (http://ifish.id/?q=id/content/about, last accessed 7 May 2021).

2.2. Data pre-processing

We first extracted GPS data from the I-Fish database and all metadata for registered boats (*e.g.* size, tonnage, home port geographical coordinates obtained through the world seaports catalogue http://ports.com/, last accessed 17 March 2020). We then cleaned the resulting dataset by removing duplicates, discarding data for short deployments (< 10 locations), and deleting points on land using high-resolution geographic data of the world's coastline through the Global Self-consistent Hierarchical High-resolution Geography, GSHHG website (https://www.soest.hawaii.edu/pwessel/gshhg/, last accessed 7 May 2021) (Wessel and Smith, 1996). Since SPOT Trace devices do not provide any geographical coordinates when trackers are turned off either voluntarily or due to empty battery (known as 'Power-off'), we assigned to those messages the latitude and longitude of the closest message in time. We discarded positions associated with consecutive 'STATUS' messages as SPOT Trace trackers send those when no activity is recorded for extended time periods. We then computed for each deployment the median time interval between consecutive messages to determine each tracker's sampling interval based on default manufacturing nominal sampling intervals (*i.e.* 2.5, 5, 10, 30, or 60 min). This calculation was required to interpolate spatio-temporal co-ordinates for positions associated with 'STOP' messages, during which vessels remain momentarily immobile, and thus may be fishing.

2.3. Port identification and trip segmentation

Prior to segmenting tracking datasets into individual fishing trips, we first had to infer port locations for each vessel. We computed for each vessel position the distance to the nearest coastline and to the nearest port, based on a list of 538 ports registered with the Indonesian Department of Fisheries. To identify vessel start and end ports for each individual trip we selected the first and last five GPS positions associated with distances to the nearest port of less than 20 km. We then identified for those subsets of points the neighbouring port with the maximum number of occurrences, or the one associated with the shortest distance in case of equal counts. All positions within 2 km of a port were assigned by default as being in port to account for potential inaccuracy in port geographical coordinates and because fishing within such a short distance from ports was unlikely due to the 50–500 m depth range at which snapper fishing occurs. Besides, waters this close to ports are most likely fished out due to their ease of access and we expect that, if fishing does indeed occur in such proximity to port, the effort is certainly marginal compared to the general fishing pattern of the fleet as corroborated visually during data exploration.

Once ports were identified, we segregated each vessel's tracking dataset into individual fishing trips. To do so, we computed the second derivative for the 'distance to port' metric (*e.g.* rate of change in distance in relation to port for consecutive messages), thereby allowing us to identify directional changes and inflection points at which vessels started moving towards or away from their port. We recorded the start and end dates for each fishing trip based on when that second derivative became positive within 2 km from port, the radius within which all positions were considered as being in port.

2.4. Vessel behaviour identification

To discriminate vessel behaviour (*i.e.* at port, steaming, or fishing), we computed and extracted metrics for each position including: distance, speed and bearing angle between consecutive locations, seafloor depth using the GEBCO one minute bathymetry grid (https://www.gebco.net/data_and_products/gridded_bathymetry_data/gebco_one_minute_grid/, last accessed 7 May 2021), distance to the nearest Exclusive Economic Zone (EEZ) boundary (negative if within an EEZ other than Indonesia's), and the Indonesian Fisheries Management Area (FMA) in which each position was recorded.

$$tw(speed) = te(Longitude, Latitude) + s(Seafloor\ depth) + s(Coast\ distance) + s(Port\ distance) + s(EEZ\quad distance) + s(Distance\ previous\ fishing\ location)$$

To identify GPS positions associated with fishing activity we then ran for each vessel a density-based multivariate spatial clustering analysis using the dbscan package in R using latitude, longitude and speed (Hahsler et al., 2019; R Core Team, 2016; Zhang et al., 2018). This procedure required us to select a suitable value of the epsilon neighbourhood, which we set at 0.25 as determined visually by quantifying the location of the knee (*i.e.* the point of maximum curvature) when plotting the k-nearest neighbour distances for each vessel's tracking dataset. Our algorithm then classified positions as 'fishing' when they belonged to geographical clusters characterised by mean speeds < 5 km. h^{-1}. All other points were classified as 'steaming' unless within 2 km of port, in which case vessel behaviour was assigned as 'at port'. Due to the absence of observers on board, AIS device, or other concomitant reliable and accurate catch data, we were unfortunately unable to validate our vessel activity predictions. Photographs were taken after catches were brought in for some vessels, however metadata for those images only included date and not time, thus preventing us from cross-referencing against predicted fishing events. Despite the lack of validation datasets, we are confident of the quality of our vessel behaviour predictions as we visually ascertained extensively the validity of our approach, and also because this dbscan spatial clustering approach has been used successfully many times historically in a fishery context (Mazzarella et al., 2014; Ramadhani and Fitrianah, 2019; Su and Chang, 2008).

We then computed summary statistics to identify patterns in fishing effort including number of trips per tracker deployment, trip and fishing event durations, distance travelled, maximum distance from port, and number of FMA visited. For each boat, we also calculated the minimum distance from each GPS position associated with fishing to previous fishing locations thus providing insights into fidelity and thus quality of fishing grounds.

2.5. Spatial analysis

To predict the geographical distribution in fishing activity and understand what factors may be influencing vessel operators to choose certain fishing grounds, we used a spatial generalised additive model (GAM), implemented through the mgcv library in R using a Tweedie exponential family for continuous non-negative data clumped at zero (Wood, 2017). Our intention was also to assess the relative influence of the following variables on vessel speed, a suitable proxy for fishing distribution for drop lines and bottom longlines when outside of ports: seafloor depth, distance to coast, distance to port, distance to EEZ, and distance to fishing grounds previously fished. In particular, the 'distance to EEZ' explanatory variable was added to the model to test the assumption that, for a subset of the snapper fleet, fishing may happen preferentially near that maritime boundary, either for compliance-related reasons or because of the intrinsic health of those distant fishing grounds. We ensured that our model was able to output stable regression estimates with low standard errors by applying a multicollinearity test between variables through computing the variance inflation factor using the '*olsrr*' R package (Aravind, 2020). While we originally explored a variety of other predictor variables, we only present hereafter the best performing model as identified by multi-model inference, based on information theoretic, *i.e.* Akaike's Information Criterion (Burnham and Anderson, 2002).

where speed is vessel speed. The term te(Longitude, Latitude) refers to a tensor product smooth fitted over a two-dimensional spatial surface, while other smoothing functions were thin-plate regression. Unfortunately, because of mostly incomplete boat metadata records in I-Fish, none of the vessels' characteristics (length, gross tonnage) could be incorporated in the above model. To quantify spatially fishing effort, we (1) ran a grid analysis, summing fishing duration across all vessels within each 0.5° x 0.5° cell, and (2) calculated the proportion of tracker deployments and fishing effort in each region of the Indonesian archipelago, as segmented geographically by Spalding et al. (2007).

3. Results

3.1. Data pre-processing

We extracted 185,585 GPS locations from the I-Fish database, collected from 294 individual deployments of SPOT Trace devices between October 2014 and December 2016, with an average deployment duration of about three months (mean ± SD = 99.4 ± 87.3 days, max = 605.6 days). Removing all duplicate locations along with points on land resulted in a dataset of 170,880 GPS locations across 278 tracker deployments. Metadata on boat length, gross tonnage and home port was only available for 25.8%, 9.5%, 39.5% of those deployments respectively, and showed SPOT Trace units were deployed on 114 distinct fishing vessels registered in 27 different Indonesian ports. Those boats were characterised by an average length of 13.9 m (SD = 4.6, range = 4.0 – 29.0 m), a mean gross tonnage of 26.7 GT (SD = 15.4, range = 1.0 – 81.0 GT). For boats whose port of origin was unknown, our algorithm inferred 26 distinct landing sites that might have been used. All ports ranged from 113.2° to 136.8°E and from 10.9°S to 1.7°N and encompassed several provinces including Jawa Timur, Bali, Nusa Tenggara Barat, Nusa Tenggara Timur, Sulawesi Utara, Maluku Utara and Papua Barat (Fig. 1). Most tracker deployments (60.2%) occurred on vessels originating from the Lesser Sunda region encompassing Bali, Nusa Tenggara Barat, and Nusa Tenggara Timur, while another 26.6% and 11.6% of trackers were deployed on boats whose ports of origin were in the Sulawesi and Banda regions respectively. Boats operating in this

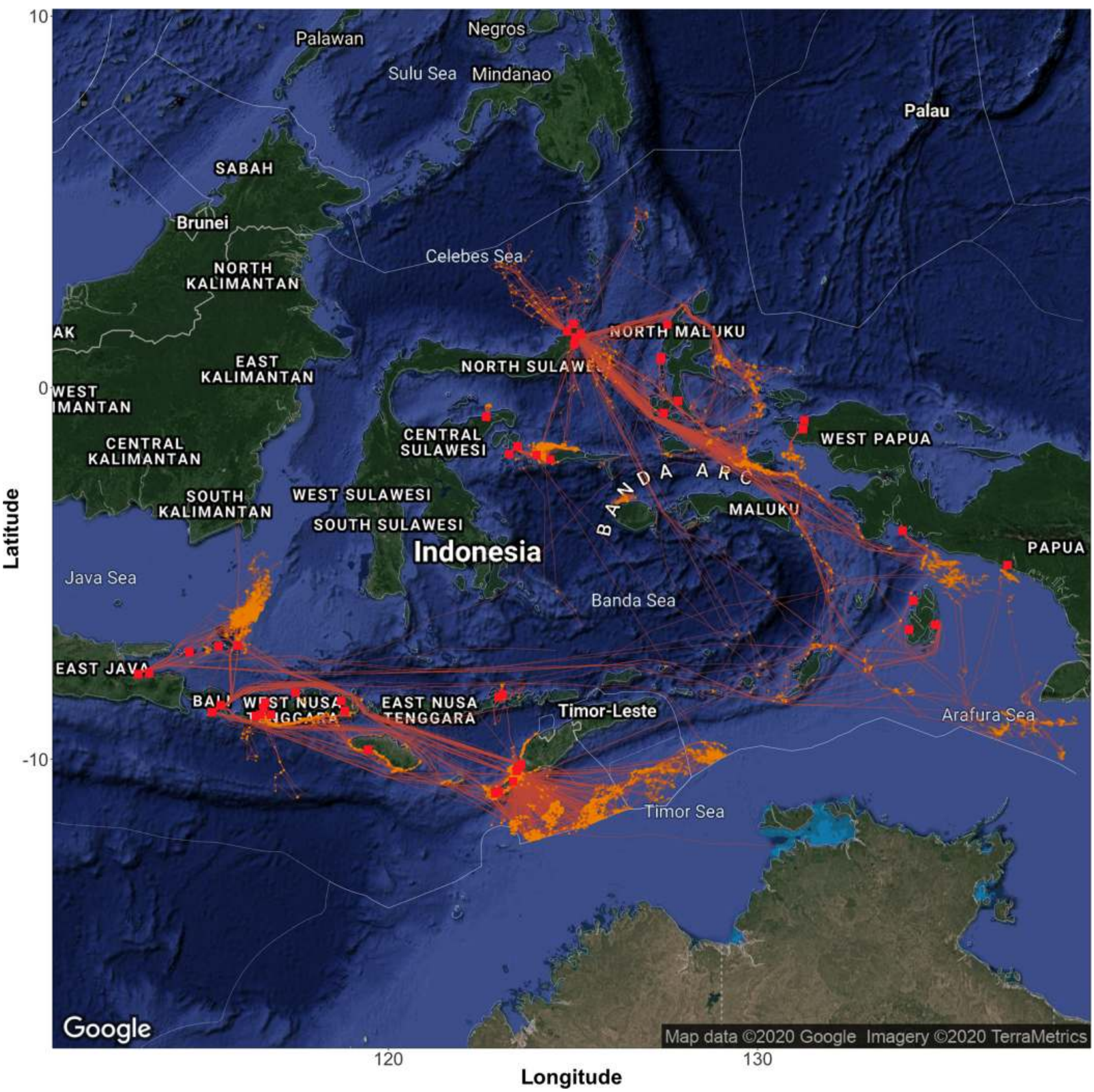

Fig. 1. Map of the study area encompassing the seas, and islands of Indonesia, Borneo, Papua, and northern Australia, built using ggmap in R (Kahle and Wickham, 2013). Vessel ports are indicated by red squares, GPS positions inferred as fishing as orange dots, and ship tracks as orange lines. EEZ boundaries are represented by white lines.

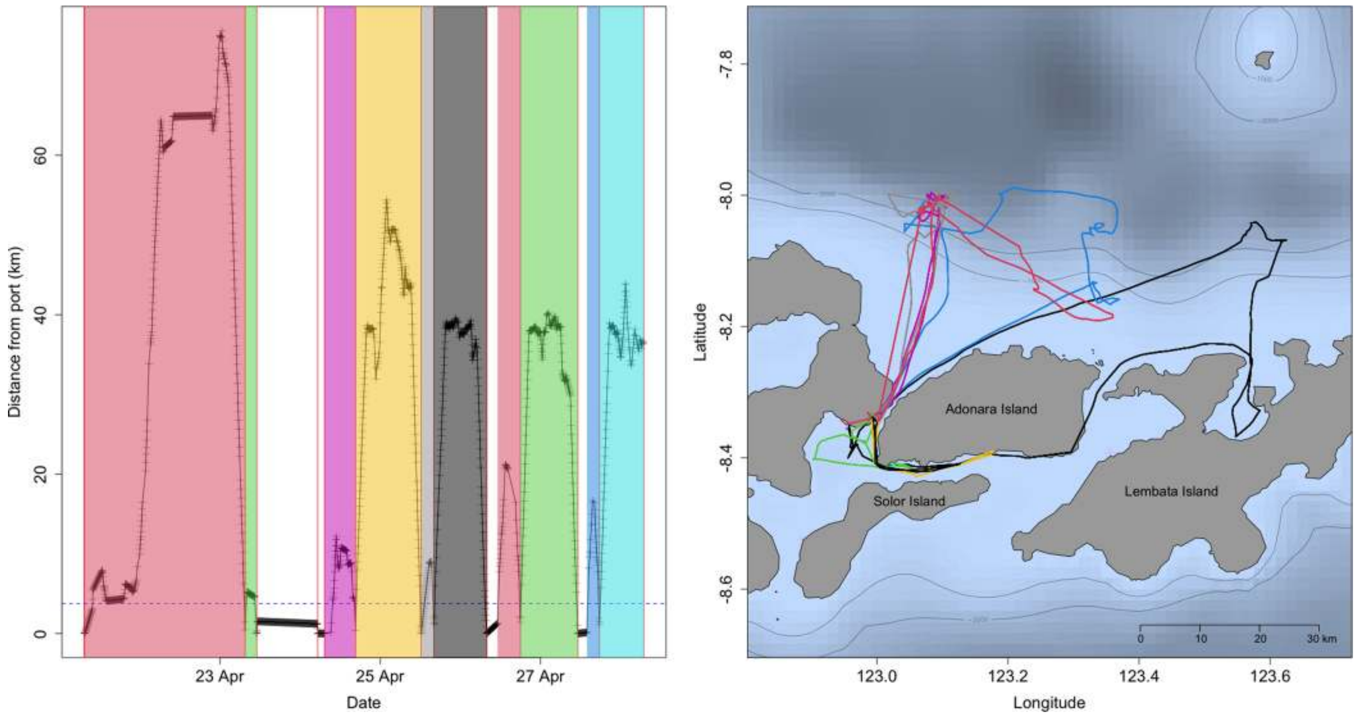

Fig. 2. Example of outputs of the track segmentation algorithm applied to GPS positions from a SPOT Trace tracker deployed on a vessel fishing off the island of Nusa Tenggara Timur, Indonesia. Left – distance from identified port as a function of time, with the horizontal blue dashed line representing the threshold distance below which a vessel is considered as being in port (5 km). Solid vertical red lines indicate breaks in the time-series data based on inflection points, while coloured rectangles show individual fishing trips considered valid for subsequent spatial and statistical analyses. Right – Map of the vessel track with distinct valid fishing trips colour-coded according to the left panel, with vessel port represented by a red cross, and bathymetric data, at a resolution of 1′ from the ETOPO1 Global Relief Model shown, including the 1000 and 2000 m isodepth contours.

deep water snapper fishery travelled primarily by following island coastlines in the South of the Indonesian archipelago and the seas around Maluku. They also displayed extensive offshore movements and fishing effort in all Indonesian seas, except in the Banda Sea where those activities were more limited and transient (Figs. 1, 4 and 5).

3.2. Vessel behaviour

Our track segmentation algorithm (Fig. 2) identified 2650 individual fishing trips, whose durations ranged from 4.3 h to 55.3 days (mean ± SD = 4.1 ± 5.8 days). The mean distance travelled per trip was 287.7 km (SD = 557.1 km) while the average farthest distance from port was 126.7 km (SD = 264.7 km), with two thirds of trips (67.3%) occurring within a single FMA. The larger a vessel's gross tonnage, the more it exhibited a tendency to have long trips far from port. For small-scale vessels (<= 10 GT) the mean ± SD trip duration and maximum distance from port were respectively 0.8 ± 0.8 days and 10.8 ± 6.5 km, while the same summary statistics for medium-scale boats (> 10 GT) were 8.1 ± 10.1 days and 301.1 ± 423.5 km. Through our spatial clustering approach, we identified fishing events with 2471 of those 2650 trips (93.2%), with a mean ± SD fishing duration of 2.1 ± 3.7 days, encompassing 44.5% of the total trip duration on average. Fishing primarily took place in relatively shallow waters (mean depth = 176.1 m, 1st and 3rd quartile = 43 and 112 m respectively), with half of all fishing events located within 20 km of land (mean ± SD distance from nearest shore = 62.5 ± 69.5 km). We observed a dichotomy in operating behaviour between vessels of lengths < = 7 m and those above, with the caveat that our results for the former group may not be representative of the overall fleet for this category due to limited sample size (n = 39 fishing events across 2 vessels *vs.* 1869 fishing events across 60 vessels respectively). Both fishing distance from land and trip duration were indeed markedly lower for vessels < = 7 m long, with mean ± SD values for these two variables of 4.5 ± 4.1 km and 36.6 ± 22.2 days compared to 46.6 ± 65.8 km and 91.4 ± 138.1 days for longer boats. Three offshore regions were intensively fished: the Jawa Timur province, the Timor Sea (including within the Australia/Timor EEZ), and the Arafura Sea along the Australian EEZ (Fig. 1). Vessels whose home ports were close to the Australian EEZ were more likely to fish close to it, as demonstrated by a linear relationship between these two variables (R^2 = 0.66). However, boats from ports up to 800 km away also fished close to the Australian EEZ border (Fig. 3). This sample of the Indonesian snapper fleet exhibited strong spatial fidelity to previously visited fishing grounds, with a median distance to previous fishing locations of 2.9 km (mean ± SD = 43.0 ± 137.2 km).

3.3. Spatial analysis

Our spatial GAM fitted on vessel speed using a Tweedie family returned a power of 1.99 indicating a Gamma distribution, and explained 26.2% of the deviance observed (Table 1). The coefficients that explained most of the deviance were the spatial interaction term (*i. e.* latitude/longitude, 11.4%), distance to port (7.3%), and seafloor depth (3.8%), with the distance to an EEZ boundary only accounting for 0.8%. This spatial modelling approach showed low speed near ships' home ports (Fig. 4). The Banda Sea experienced little boat traffic (Fig. 1) while other areas, including the Java, and Timor Seas, attracted large numbers of vessels which exhibited slow speed movements likely due to fishing events (Figs. 1 and 4). Furthermore, examining fishing event distribution at the regional level revealed some geographical discrepancies in how vessels operate. Boats from Nusa Tenggara primarily fished around the Timor coast, and further South in the Timor Sea, particularly along the Australian EEZ and in the joint regime Australia – East Timor EEZ area (Figs. 1 and 4). While vessels from Bali and Jawa Timur provinces also fished near the Australian EEZ and in that joint regime, their primary fishing grounds were in the Java Sea, North of Bali and South off West Nusa Tenggara (Figs. 1 and 4). Fishing by boats

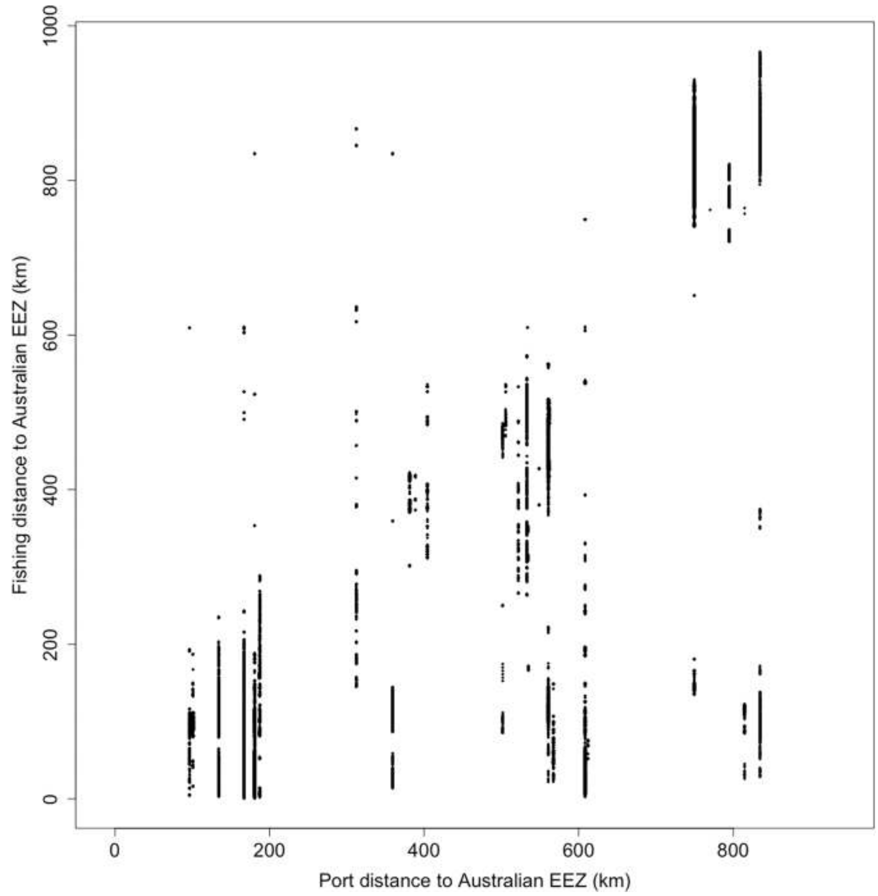

Fig. 3. Propensity to fish near the Australian EEZ for boats whose home port's closest EEZ border was Australia's.

Table 1
Parameter estimates and significance of the spatial generalised additive model (GAM) for vessel speed. SE = standard error; CI = confidence interval; df = degree of freedom. Note that values for coefficient, SE and t-value are not available for smoothing terms.

Parameter	Coefficient	SE	t-value	df	p-value
Parametric terms					
Intercept	1.139	0.004	289.5	1	< 0.001
Smoothing terms					
Longitude, latitude				29	< 0.001
Seafloor depth				9	< 0.001
Coast distance				9	< 0.001
Port distance				9	< 0.001
EEZ distance				9	< 0.001
Distance previous fishing location				9	< 0.001

originating from the Sulawesi Utara and Maluku provinces mainly took place close to port, although substantial fishing activity occurred in the Celebes Sea and in the Banda Arc (Figs. 1 and 5). Boats from Papua Barat fished close to port, though fishing also occurred near the Australian EEZ boundary in the Arafura Sea (Figs. 1, 4 and 5). Fishing effort was consistent with the provenance of vessels. The most intense activity occurred in the Sunda region (South of Bali, Nusa Tenggara Barat, Nusa Tenggara Timur) encompassing 42.6% of all fishing events' duration, followed by 18.2% and 15.1% in the Sulawesi and Banda Sea North of Maluku respectively (Fig. 5).

4. Discussion

4.1. SPOT Trace: a suitable low-cost technology to investigate fishing effort

This pilot project demonstrated that SPOT Trace trackers can be used as a low-cost VMS substitute. We were, indeed, able to quantify the spatial distribution and intensity of fishing in a subset of the Indonesian snapper fleet, using an automated procedure encompassing port identification, trip segmentation and spatial clustering algorithms. Through GPS data acquired by SPOT Trace devices, it is possible to gain a detailed understanding of how unregulated fisheries operate, and eventually estimate the number of fishing days which is notoriously difficult to derive for such dispersed fisheries (FAO, 2020). Documenting the spatio-temporal use of fishing grounds is also critical to determine accurately how much pressure is being put on marine ecosystems and stocks. Such information is particularly lacking for developing countries with fishing fleets exempt from fishery management instruments as monitoring activities and regulations are typically fewer than for developed nations (FAO, 2020). Nevertheless, while we visually ascertained by looking at predictions from our spatial clustering approach that SPOT Trace is a suitable technology for classifying vessel activity and subsequently derive fishing-related metrics, we could not quantify the accuracy of our behavioural predictions due to the absence of concomitant information. This validation step, using catch data (*e.g.* timestamped photos of catch when fish are brought on board, logbook, observer, or electronic monitoring records), is essential to estimate the error rate associated with our fishing prediction algorithm and compare its accuracy against other analytical approaches, such as random forest models, which have been previously used on datasets collected from GPS trackers deployed on small-scale fisheries (Behivoke et al., 2021). While

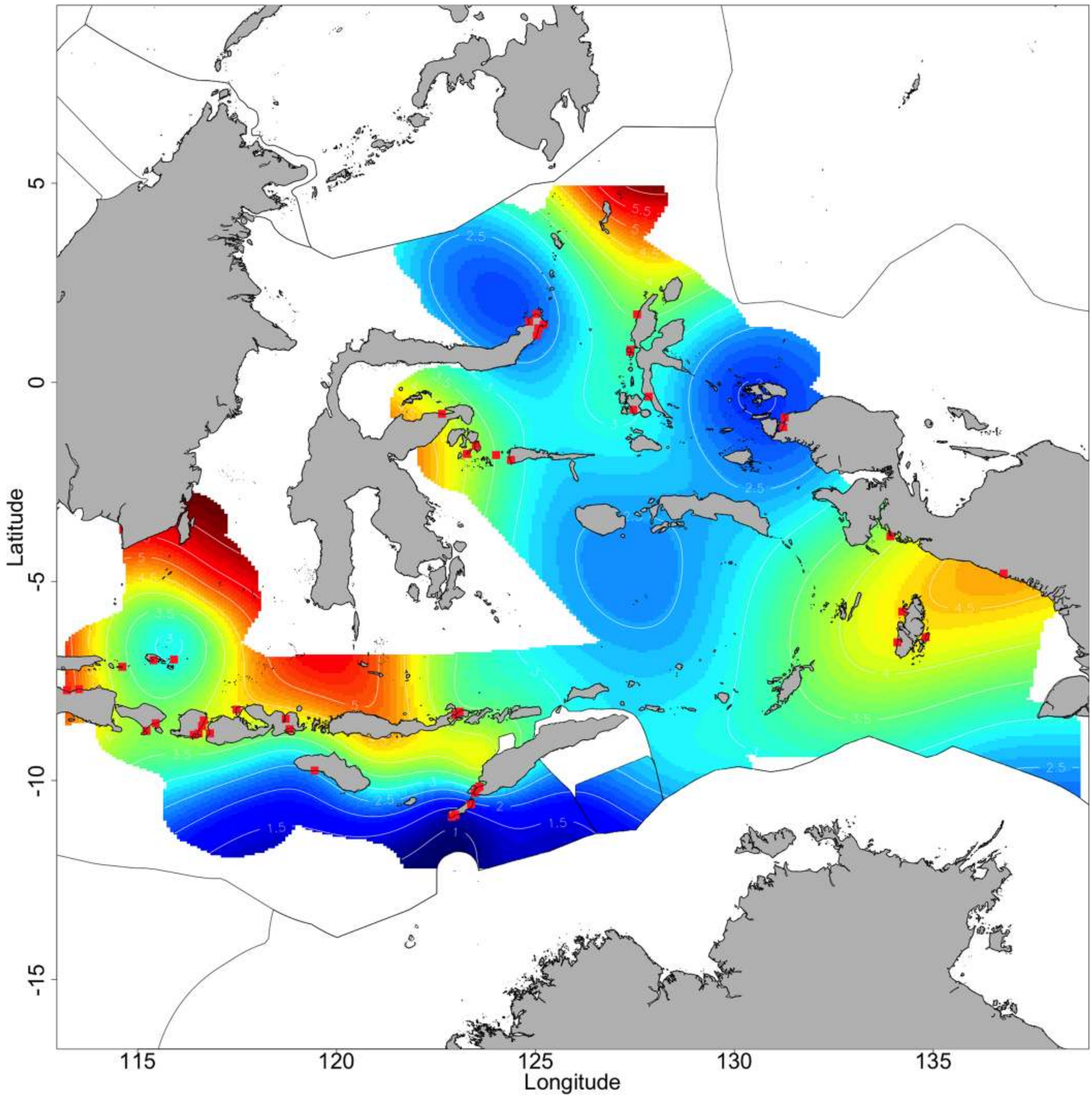

Fig. 4. Colour gradient contour plot of modelled vessel speed in km.h^{-1} as predicted by fitting a spatial generalised additive model to SPOT Trace GPS coordinates using a Tweedie exponential family. Vessel speed, a proxy for fishing distribution, is colour-coded so that low speeds are shown in blue, while high speeds are in red. Latitude and longitude were included as a smoothed interaction term, conditional on vessels not being in ports, to account for non-linear spatial heterogeneity. Port locations and EEZ boundaries are respectively represented by red squares and thin black lines.

using SPOT Trace units for monitoring vessel behaviour and quantifying fishing effort may be far-reaching due to its low cost, we foresee that its main application would be in developing countries on commercial vessels not equipped with traditional VMS hardware. Moreover, using similar analytical techniques, there is potential to expand this scope to subsistence and recreational fishing as both remain largely unquantified (FAO, 2020). SPOT Trace units, however, do have limitations, particularly their short battery life of only 14–30 days period when using hourly or at higher frequency (Natsir et al., 2019). The required routine operation of battery changing may also be detrimental to the watertight rubber seal between the battery compartment and the mother board, thus compromising the device's integrity and reliability. SmartOne Solar (Globalstar, Covington, LA) constitutes an alternative, solar-powered, personal tracker solution enhanced functionalities compared to SPOT Trace devices (albeit three times more expensive), with better durability of up to ten years along with a special switch to prevent the unit being turned off.

4.2. *Voluntary data to understand risk and identify potential violations*

We observed three contexts in which SPOT Trace tracking devices revealed patterns that are of relevance for compliance. First, while the

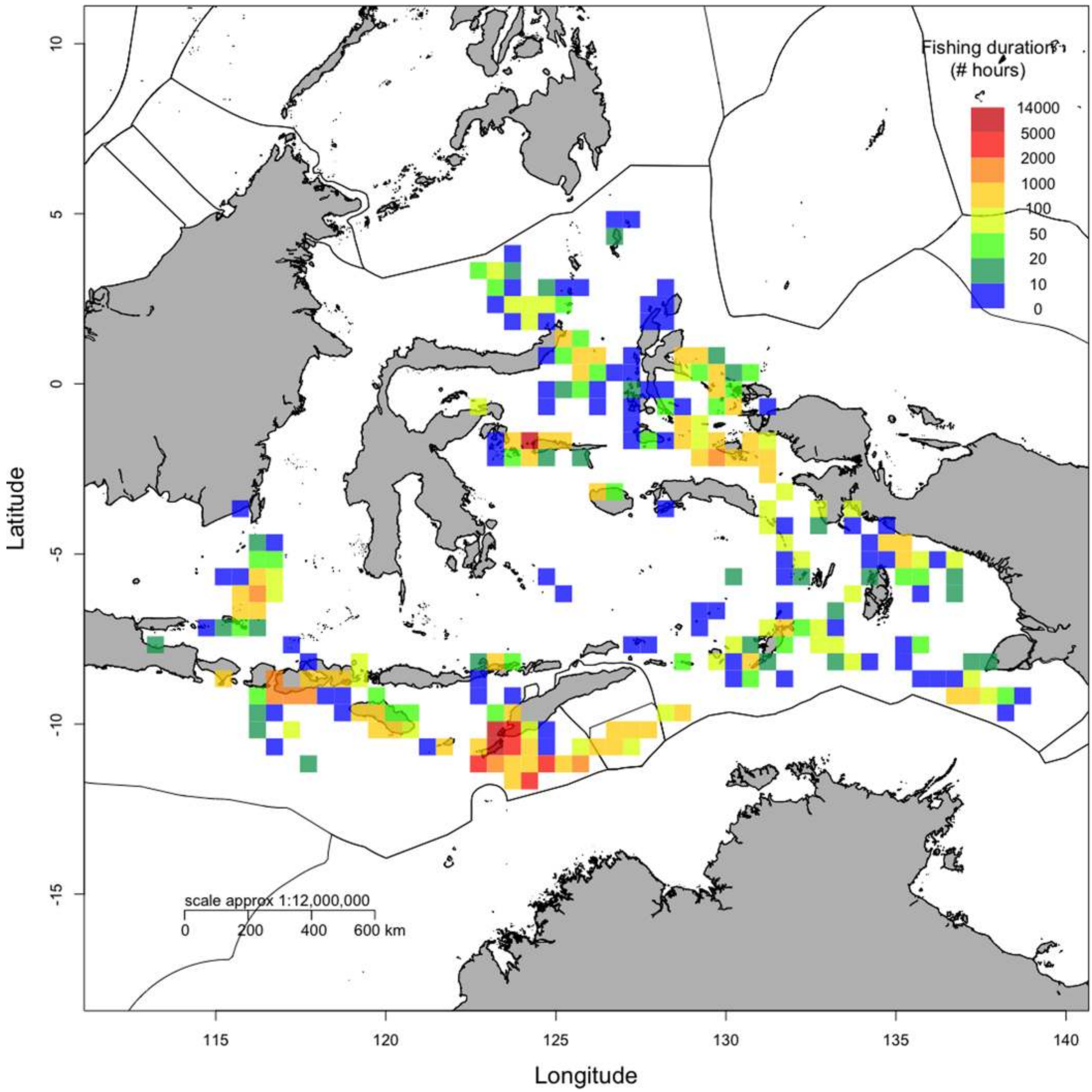

Fig. 5. Total fishing duration (hours) for the Oct. 2014 – Dec. 2016 period per 0.5° grid cell. EEZ boundaries are represented by thin black lines.

majority of fishing trips took place in a single fishery management area, one third encompassed two or more of those areas. This behaviour demonstrates that operators rely on multiple fishing grounds within a season and therefore do not necessarily comply with regulations requiring them to fish solely within their designated management area (s). Second, there was an abundance of vessels fishing near the the Australian EEZ boundary. There is a history of compliance issues in this region, with unauthorized vessels crossing into Australian waters to fish (Edyvane and Penny, 2017; Vince, 2007). Tracking devices clearly showed a high risk of this pattern in a particular section of the border south of Timor. Third, power-off messages may sometimes indicate an intent to knowingly violate fisheries regulations. For instance, our tracking data showed an obvious cluster of voluntary power-off messages from vessels operating along the Australian EEZ border.

However, there are a number of limitations with using a voluntary tracking system as a compliance tool. First, there must be an incentive for fishers to participate. For instance, the complementary communication and safety function of the SPOT Trace device is a privilege that vessel operators may lose if their tracking units fail to provide data (*e.g.* due to insufficient care or frequent 'Power-off' messages). Second, any compliance estimates may be overinflated, as non-compliant vessels are much less likely to participate. While the frequency of fishing at the Australian border and power-off messages are particularly high for Timor-based vessels, which aligns with historic non-compliance observations, this pattern may not represent the picture that would emerge if all vessels were tracked. Indeed, as vessel operators volunteered to participate in this program, there may be a substantial selection bias, making it difficult to estimate how representative the activity we observed is in relation to the entire deep water snapper fleet.

4.3. Spatial distribution of fishing effort deep water snapper fleet

Fishing for the Indonesian snapper fishery primarily occurred a short distance off islands, and in the Java, Timor, and Arafura Seas. This distribution of effort may be explained by the fact that (1) the snapper fishery uses handlines, droplines and bottom longlines between depths of 50–500 m, and (2) operators try to minimise travel from port to reduce fuel consumption. What is remarkable though is the fishing intensity in the offshore regions mentioned above, attracting vessels from distant provinces. Such long-distance trips imply that it may be more beneficial economically for operators from certain ports (*e.g.* Jawa Timur, Bali) to use large volumes of petrol than to fish locally. This spatial distribution may reflect the potentially depleted state of snapper stocks, at least in some coastal parts of the Indonesian archipelago (Amorim et al., 2020). Alternatively, the quality of such offshore fishing trips may be higher than their coastal counterparts, thus outweighing the comparatively expensive travel-related cost. Social research involving surveys of fishermen and accounting for boat characteristics (GT, gear type) and species' historical spatiotemporal distribution or expected habitats could help establish whether fishing distance from port is indicative of stock health for target species. Similarly, linking data on fish size, species composition, and catch rates with fishing trip distance and effort could indicate whether tracking data may be used to compile an inexpensive index of stock status on individual reefs.

On a positive note, in this study, vessels were typically at sea for a few days, travelling relatively small distances (median distance travelled per trip = 59.7 km) and fishing mostly close to port. These statistics, along with the high level of spatial fidelity to fishing grounds vessel operators demonstrated, most often returning to fish within 20 km of a previous fishing event, may indicate that the majority of coastal waters in our study area still contains suitable snapper fishing grounds for viable commercial exploitation. Spatial patterns are insufficient, however, to draw definite conclusions on stock status thus further assessments are required to test our hypothesis. The primarily coastal fishing behaviour we observed may, alternatively, be an artifact of our sampling regime. The latter, while unfortunately largely unknown to us, may have been biased towards deploying preferentially trackers on small vessels, which almost exclusively exploited inshore waters compared to boats whose lengths were greater than seven metres and ventured markedly further offshore. Moreover, given the substantial number of vessels operating in the Indonesian snapper fishing fleet (close to 11,000 boats in 2020) and our reduced sample size of 114 vessels, the representativeness of our results is inherently questionable. Our findings, indeed, rather serve to reveal general, nation-wide fishing patterns and demonstrate the applicability of our experimental approach for fishery management and surveillance purposes than unveil the granularity in operations at different spatial scales across multiple gear types and vessel characteristics. The archipelago-wide transiting practices of snapper fishers observed in this study should, nevertheless, act as a reminder that fish resources are limited and that operators may readily abandon their traditional fishing grounds if depleted to reach new, farther fishing grounds in the hope of improving catch rates. Without appropriate policing, management and innovative low-cost monitoring tools like SPOT Trace, the future of the Indonesian snapper fishing industry may indeed change from a once coastal-restricted fishery to a strictly offshore one involving higher risks, increased transport cost and emissions, and reduced profitability, as already observed in many fisheries around the world (Rousseau et al., 2019).

CRediT authorship contribution statement

Xavier Hoenner: Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Peter Mous**: Conceptualization, Methodology, Data curation, Resources, Project administration, Funding acquisition, Writing – review & editing. **Erland Barlian**: Writing – review & editing. **Lilis Sadiyah**: Writing – review & editing. **Tri Ernawati**: Writing – review & editing. **Duranta Diandria Kembaren**: Writing – review & editing. **Fayakun Satria**: Writing – review & editing. **Britta Denise Hardesty**: Conceptualization, Methodology, Writing – review & editing. **Chris Wilcox**: Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The dataset analysed as part of the present study is confidential and thus cannot be made publicly available.

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