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Ocean-scale footprint of a highly mobile fishing fleet: Social-ecological drivers of fleet behaviour and evidence of illegal fishing

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Abstract

1. Managing the footprint of highly mobile fishing fleets is increasingly important due to continuing declines in fish populations. However, social-ecological drivers for fisher behaviour remain poorly understood for many fleets globally.
2. Using the Sri Lankan fleet as a case study, we explored the role of social, environmental and policy drivers of effort distribution and illegal fishing. We used semi-structured interviews and participatory mapping with 95 fishers, combined with explanatory modelling (GLM) and multivariate statistics, including principal component analysis (PCA).
3. Our findings highlighted the broad footprint (~3,800,000 km^2) of this fleet, with fishing effort expended in high seas (53.9%), domestic (40.9%) and, illegally, in foreign waters (5.2%). Twenty-six per cent of fishers directly admitted to fishing illegally in foreign waters during interviews, whereas 62% of fishers indicated doing so during participatory mapping.
4. GLMs explained underlying decisions of where to fish (36% of the total deviance in effort distribution) as a function of social variables (14%), notably distance from landing sites (13%), and environmental variables (11%), notably sea surface temperature (10%).
5. Multivariate analysis revealed that individual fisher characteristics associated with illegal fishing, such as a level of reliance on sharks, vary across the fleet. The analysis of qualitative data suggested that the influence of interpersonal and community social networks and perceptions of higher catch value, particularly of sharks, may be important.
6. Our approach demonstrated the utility of mixed methods research, including the collection of qualitative data, for creating a detailed understanding of spatial behaviour, including decisions of whether to fish illegally.
7. Results highlighted the importance of adopting a social-ecological lens to investigate drivers for human behaviour and non-compliance with rules. We advocate for

a nuanced approach to monitoring and managing of fleets, including investigating localised social drivers for illegal fishing and enhancing regional transparency in fleet monitoring.

KEYWORDS

conservation rule-breaking, illegal, unreported and unregulated, Marine Protected Areas, participatory methods, sharks, Sri Lanka

1 | INTRODUCTION

As a consequence of depleted coastal fish populations, many fleets are expanding beyond national Exclusive Economic Zones (EEZs) to high seas areas (Sumaila et al., 2015; Tickler et al., 2018). If inadequately monitored and managed, this can lead to overfishing, particularly of economically valuable migratory species, such as tunas (McWhinnie, 2009; Pons et al., 2018), and vulnerable species, such as elasmobranchs, which are frequently caught as bycatch (Campana, 2016). Therefore, understanding and managing the spatiotemporal fishing pressure of highly mobile fleets is paramount for protection of ocean diversity (Branch et al., 2006; Van Putten et al., 2012).

Spatial management policies, including Marine Protected Areas (MPAs), are increasingly proposed as a way of managing fishing effort distribution, and plans to protect all or some of the high seas in this manner are currently being debated (Sala et al., 2018; Sumaila et al., 2015). However, the attainment of expected social-ecological benefits from these policies is highly reliant on human responses, including adherence and willingness to change fishing behaviours (Castrejón & Charles, 2020). Notably, illegal incursion of foreign fleets into designated management areas, including EEZs, is an ongoing problem for many countries globally (Arias et al., 2016; Bergseth et al., 2015). In order to predict and manage the compliance of fleets, a detailed understanding of what social factors motivate spatiotemporal distribution of fishing effort is required (Castrejón & Charles, 2020; Sutinen & Kuperan, 1999). We define 'social factors' from hereon as including both social and economic considerations.

Identifying which social factors are of importance on a fleet-specific basis can be difficult and time-consuming, leading them often to be poorly considered in understanding of spatial and compliance behaviour of fleets (Kaplan et al., 2010; van Putten et al., 2012). This can contribute to unintended feedback behaviours, including the displacement of fishing effort to more vulnerable areas, or non-compliance with spatial management policies, such as MPAs, due to confusion or a lack of alternatives (Castrejón & Charles, 2020; Mizrahi et al., 2019). Historically, behaviours were primarily explained by economic drivers (Sutinen & Kuperan, 1999). For example, profit maximisation and compliance theories, which both imply that fishers will make decisions, either individually or collectively, that achieve the greatest difference between revenue and costs (Branch et al., 2006; Hilborn & Kennedy, 1992; Robinson & Pascoe, 1997; Sumaila et al., 2006). However, research now increasingly recognises the importance of other social factors such as social networks or traditions and expertise of fishers (Belhabib & Le Billon, 2020; Béné & Tewfik, 2001; Klain & Chan, 2012; van Putten et al., 2012). Accordingly, fisheries and conservation research increasingly advocates for better integration of broader social factors (Fulton et al., 2011; Solomon et al., 2020).

New technologies, including Vessel Monitoring Systems (VMS) have made it easier to characterise and track spatial behaviour and to identify non-compliance (Joo et al., 2015). VMS is generally considered well-adopted within regulations pertaining to high seas fleets, as a legal prerequisite for vessels engaging in high seas activities across many countries (Dunn et al., 2018). However, the understanding of spatial movement for some fleets remains hindered by non-compliance with, or slow adoption of VMS regulations (Thiault et al., 2017). Collecting participatory data from fishers can provide a complementary data source (Shepperson et al., 2014). Participatory mapping, a term which encompasses approaches and techniques that capture spatial knowledge, including historical behaviours and perceptions, is increasingly applied in marine social-ecological research (Kafas et al., 2017; Selgrath et al., 2018). By capturing fisher perceptions of marine spaces and social drivers for behaviours, it can help to predict and manage human responses to spatial management (Brown & Weber, 2012; Cinner et al., 2014). Yet, it remains underused for highly mobile fishing fleets (Moore et al., 2017).

In this study, we combined participatory and qualitative data collection methods with geospatial statistics, in order to map and understand the spatial distribution and compliance of the Sri Lankan offshore fishing fleet. This fleet is known to operate over a large ocean area and is suspected of relatively high levels of illegal fishing in foreign EEZs (FEEZs, hereafter referred to simply as 'non-compliance'). Firstly, we used participatory mapping and semi-structured interviews to identify the spatial footprint of the fleet. Secondly, we quantified the potential role of social, environmental and spatial management policy (herein referred to as 'policy') variables on fishing activity by building explanatory GLMs. Thirdly, we used analysis of qualitative data to explore social variables affecting non-compliance and used multivariate statistics, including Principal Component Analysis (PCA), to identify vessel and fisher characteristics that may be diagnostic of higher risk of non-compliance. We compare our results with existing knowledge of behaviours for this fleet and discuss the importance of our findings within the context of national and regional policy and management.

2 | METHODS

2.1 | Case study

This study considers the semi-industrial fleet of Sri Lanka, locally referred to as multi-day vessels or 'IMULs' (herein 'IMULs'). IMULs are medium-sized vessels (9–17 m), operated by crews of three to 10 men who typically target high-value pelagic species, such as tuna and sharks, using gillnets and/or long-lines (Collins et al., 2020). Equipment on-board vessels are broadly homogenous, with all vessels reliant on ice-holds to store catch and an absence of advanced technologies, such as fish finders. In 2018, there were 4,508 IMULs, operating from ~14 harbours in Sri Lanka, of which 1,346 were licensed for high seas fishing (National Fisheries Data, 2019). To operate in high seas, vessels are required to hold a High Seas Licence (HSL) and operate a functioning VMS. While characteristics such as vessel size and desired economic returns are thought to be important, drivers of spatiotemporal effort for this fleet remain poorly understood (Amarasinghe, 2013).

Recent analysis of VMS data from this fleet shows a broadly compliant fleet with a wide spatial footprint, reaching distant waters such as Somalia and Mauritius (Gunasekara & Rajapaksha, 2016). However, IMUL vessels have been repeatedly arrested for illegally fishing in foreign waters, such as Seychelles, India and British Indian Ocean Territory (BIOT), over the last three decades (Amarasinghe, 2013; Hays et al., 2020; Tickler et al., 2019). Given this inconsistency, there is a perceived need for alternative approaches to collecting data on fleet behaviour. This is particularly critical when considering the implications of non-compliance for sustainable development. Notably, in 2014 the European Union introduced sanctions following continued evidence of non-compliance, banning the imports of seafood valued at $90 million per annum in 2013 (European Commission, 2014; Sri Lanka faces EU fish export ban, 2014). More broadly, non-compliance has been shown to erode the effectiveness of spatial management policies, such as MPAs, and threaten global fisheries sustainability (Sumaila et al., 2020). Accordingly, the illegal activity of IMULs has been blamed for dramatic population declines in sharks in BIOT MPA (Graham et al., 2010; Tickler et al., 2019).

2.2 | Study approach

We selected two sites on the south and west coasts of Sri Lanka that had reported connections to illegal fishing (Martin et al., 2013). Sites for this study are defined as places for landing and berth of IMUL vessels with associated facilities, including commercial fish markets. Cumulatively, 9% of all nationally registered IMULs land to both sites and they are roughly similar in terms of size (5% and 4% land to sites 1 and 2 respectively) and associated facilities (National Fisheries Data, 2019). Due to the sensitive nature of collected data, site names and locations are anonymised throughout.

We used two main methods concurrently, namely semi-structured interviews and participatory mapping. Data were collected over 32 days from June to August 2019 by three Sri Lankan researchers (co-authors IW, DW and AB, affiliated with Sri Lankan NGO Oceanswell), who were trained in-situ over a 1-month period, during which methods were also piloted with 10 fishers. Only fishers in charge of vessel navigation (i.e. skippers) were investigated, as preliminary results suggested they were more comfortable with spatial data than other crew members.

All methods and interviews were carried out in Sinhalese, and ethical approval was granted by the University of Exeter board (Ref: eCORN001727 v4.1). Insights generated from qualitative and quantitative data were combined in an iterative manner throughout data processing (Figure 1). Findings from both data types are presented together for some of the results section. For example, fisher quotes identified from analysis of qualitative data are used to contextualise and support findings derived from quantitative data. All data processing and analysis were carried out by the first author.

2.3 | Data collection

Using convenience sampling, a form of non-probability sampling used to select participants (Newing, 2010), researchers approached fishers at sites and explained project purpose, anonymity and confidentiality. All study participants gave verbal informed consent

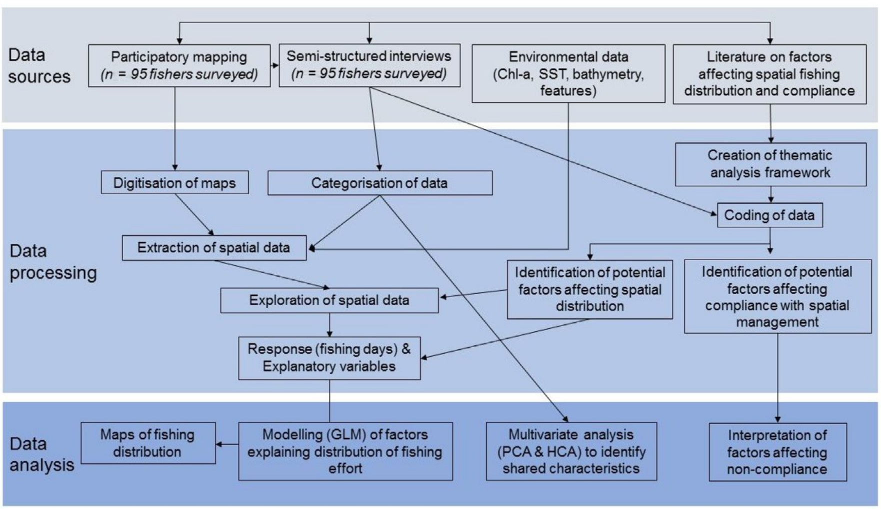

FIGURE 1 Workflow schematic showing individual steps involved in data collection and processing to map spatiotemporal effort and identify social, environmental and policy drivers for behaviour, including non-compliance

(participants may have been uncomfortable with written consent). Then, individual fishers (n = 95) completed a mapping exercise and semi-structured interview in a quiet area. The mapping exercise collected information on: (a) spatiotemporal effort, (b) perceived economic importance of fishing areas and (c) proportional contribution of target and bycatch species, pertaining to the time period 2014–2019 (additional details in Supplementary Detail (SD) 1: Data collection). The semi-structured interview, comprised of 35 open-ended and closed questions, collected information on: (a) socio-demographics of fishers, (b) vessel characteristics, (c) vessel fishing strategy and (d) fisher perceptions of governance and management (Table S1). With fisher permission, dialogue was audio recorded during both methods (average duration was 42 min, range was 28–57 min), and researchers prompted fishers to explain their answers throughout, in order to provide an additional source of qualitative data in the form of conversation transcripts. Following data collection, all recordings were transcribed and translated to English.

Due to the sensitive nature of data, there was a high likelihood of both response bias, giving an answer perceived as desirable to the facilitator, and non-response bias, refusing to answer all or some questions (Arias et al., 2015). We mitigated this by explaining that data were collected for a student project, by asking sensitive questions towards the end and by cross-method triangulation, which uses multiple methods to address bias created by one and broaden perspectives gained on an issue (Bryman, 2016; Travers et al., 2019). Further details are included (SD 2: Methodology considerations).

2.4 | Thematic analysis framework

In order to identify important social, environmental and policy variables for further analysis, we reviewed key scientific literature on spatiotemporal effort of fisheries (Bertrand et al., 2007; Castrejón & Charles, 2020; Daw, 2008; Kellner et al., 2007) and compliance with spatial management policies (Arias et al., 2015; Béné & Tewfik, 2001; Hall-Arber et al., 2009; Van Putten et al., 2012; Raemaekers et al., 2011; Read et al., 2011). This review was also used to build a thematic analysis framework (Table 1) for the purpose of analysing qualitative data.

2.5 | Analysis of qualitative data

In order to generate insight into important variables that may affect spatial behaviour and non-compliance for this fleet, qualitative data were coded against our thematic analysis framework (Table 1). Data from mapping transcripts and interviews were compiled and coded within NVivo software (NVivo, 2020). Coding was conducted in an iterative manner, whereby codes within the thematic analysis framework can be re-arranged hierarchically and redefined multiple times if they do not fit the data (Bryman, 2016). This process continued until we were satisfied no new meaning or interpretation can be gleaned from data analysis, a process called data saturation (Newing, 2010). Findings are presented throughout the results section to contextualise quantitative data, and separately to illustrate insights generated regarding non-compliance.

2.6 | Processing spatial data

A database of fisher and vessel characteristics was built from interview data, creating categories for non-continuous and non-numerical data and assigning numerical values (a process called dummification) (Bryman, 2016). Categories were created after initial familiarisation with the data, and re-evaluated and redefined throughout data processing in an inductive approach. Then, fisher maps were digitised (using geo-referencing tools) and created as individual shapefiles (n = 95) using QGIS (QGIS.org, 2020). Data pertaining to fishing activities, taken from the mapping activity, were related to geographical location. In order to understand compliance with spatial and management policies, proportion of annual effort expended within FEEZs (%) was calculated for each fisher using an overlap analysis tool in QGIS. Shapefiles were combined and overlaid with a grid, with 0.5° resolution at the equator (an area roughly equivalent to ~2,500 km^2), chosen as a trade-off between obtaining the highest spatial resolution and minimising spatial autocorrelation (Cabanellas-Reboredo et al., 2014).

Through our literature review and thematic analysis of qualitative data, we identified potentially important social variables (see Table 2). Data for these were extracted from interview and mapping data for each grid cell. Environmental variables were accessed (see Table 2) and extracted using the RASTER package in R (Hijmans & van Etten, 2020). For policy variables, jurisdiction for each cell was designated by generating a categorical variable, as a function of whether it was within domestic (Sri Lankan EEZ), high seas or foreign country waters.

2.7 | Modelling of spatiotemporal effort

We modelled spatiotemporal effort using total number of fishing days (per grid cell) as the response variable (rv). This was calculated by multiplying proportion of total annual fleet effort per grid (%) by total number of fleet fishing days summed for all sampled vessels (n = 21,280 days).

$$\text{fishing days (rv)} = \frac{\sum (\text{annual fishing per grid})}{\sum (\text{annual fishing effort for all grids})} \times \text{total fishing days.}$$

Data exploration, guided by a protocol designed to minimise common statistical errors, was then conducted to detect outliers, heterogeneity of variance, collinearity and dependence of observations following the recommendations of Zuur et al. (2010). Our protocol included (a) linear modelling to confirm a significant effect, (b) boxplots

TABLE 1 Thematic analysis framework used to identify important variables that influence spatiotemporal effort and non-compliant aspects of fisher behaviour. This framework was used for analysis of qualitative data

Category	Subcategory	Description
Framework 1: Identification and interpretation of factors explaining the spatial distribution of vessels		
Factors explaining spatial distribution	Social	Governance and management, *incl. licensing regulations, perceptions of management, subsidies*
		Facilities and equipment, *incl. limitations and possibilities of vessel equipment, impact of landing and market facilities*
		Expected value of catch, *incl. expected catch volume and quality and microeconomics (such as market value and dynamics)*
		Fishing costs, *incl. breakdown and effect of costs*
		Social networks, *incl. communication between fishers, organisation of vessel networks and coordination during fishing activities*
		Historical fishing practices, *incl. site fidelity, traditional fishing knowledge and practices*
	Environmental	Bio-ecological factors, *incl. target species distribution, geomorphology of fishing areas*
		Climatic factors, *incl. seasonality, weather and climate conditions*
	Spatial policy and management	Effect of spatial-based regulations, *incl. response to regulations, displacement of effort, fishing the line and rate of incursions*
Framework 2: Identification and interpretation of factors explaining compliance with spatial management policies		
Factors affecting non-compliance	Economic gains	Perceived benefits of non-compliance, *incl. expected catch volume and quality, change to fishing time and associated costs*
	Economic necessity	Perceived necessity of non-compliance, *incl. accrued debt, reliability of income, effect of vessel costs*
	Costs	Costs associated with non-compliance, *incl. risk of capture, sanctions levied, loss of future economic gains*
	Species-specific targeting behaviours	Influence of target species, *incl. fishing site locations, expected catch*
	Social norms	Injunctive norms, *incl. perceptions of which behaviours are typically approved or disapproved, within immediate interpersonal networks (such as on a vessel) and within the wider community*
		Descriptive norms, *incl. perceptions of other behaviours, perceptions of acceptability of non-compliance*
	Social networks	Interpersonal and wider community networks, *incl. sharing of knowledge and coordinated nature of behaviours*
	Corruption	Corruption, *incl. presence and ability to ameliorate social cost of non-compliance*
	Behavioural and psychological	Behavioural attributes of fishers, *incl. attitudes towards risk-taking and non-compliance*

(categorical factors) and dot charts (continuous factors) to look for potential outliers, (c) histograms and Q–Q plots to assess variable normality and (d) pair plots to assess variable collinearity. In order to check for collinearity, a correlation coefficient matrix and correlation scatterplots were created (SD 4). To check for redundancy and multicollinearity, variance inflation factors (VIFs) were calculated (SD 4). Social variables were also visualised spatially to look for spatial distribution patterns (Figure S1). Data exploration led to vessel size, cost of fishing and distance to FEEZ being excluded from modelling.

Fisheries effort was right-skewed (see Figure S2 for response variable distribution) and was therefore modelled using GLMs with a Gaussian family and 'log' link function. All models were run with R statistical software (R Core Team, 2020). Using the MuMIn package (Barton, 2020), we employed the step function to perform backward model selection, using each model's Akaike Information Criterion (AIC) adjusted for sample size (AICc) as the selection criterion to choose the most parsimonious model. Alternative models, with a delta AIC (Δm) ≤2 were compared with each other and a null model (intercept only; Table S3). Standardised coefficients were calculated for the best models to compare effect sizes, and partial residual plots used to visualise effects. Deviance explained was calculated for each GLM.

To account for potential spatial autocorrelation (SAC), we implemented the residuals autocovariate (RAC) approach (Crase et al., 2012). Following model selection, residuals were calculated for each grid and used to compute the autocovariate, a measure of similarity between the value of the rv at a location and neighbouring locations, by a focal calculation. The autocovariate is included as an additional variable and modelling run again. A Moran's test, on model residuals, confirmed the RAC method was successful in accounting for SAC ($p < 0.001$).

In order to determine the relative importance of each variable, we calculated Akaike weight (AICw) across all models, by creating all possible submodels (dredge function, MuMIn package) from the full model (containing all variables). This gives a value of 0 (variable not deemed useful within models) to 1 (essential variable across all

TABLE 2 Hypothesised explanatory variables based on data exploration and key relevant literature analysis used in the modelling of spatiotemporal distribution of fishing effort (days)

Category	Name	Description	Supporting evidence	Source
Social	Catch worth	average catch worth ($)	Thematic analysis of qualitative data	Derived from primary data
	Distance to site	distance of grid to the landing site(s) (kilometres)		
	Shark reliance	proportion of fishing effort allocated for sharks (%)		
	Vessel size	average size of vessels (metres)		
	Cost of fishing	average cost of fishing ($)		
Environmental	Chlorophyll *a* (median)	an indicator of primary productivity and available trophic energy (mg/m^3)	Currie et al. (2004) and Rolim and Ávila-da-Silva (2018)	NASA (2020a)
	SST (median)	a proxy for latitudinal patterns in species diversity universally observed across taxa (°C)	Tittensor et al. (2010) and Friedland et al. (2020)	NASA (2020b)
	SST (standard deviation)	an indicator of frontal dynamics generating nutrient mixing and multilevel productivity (°C)	Queiroz et al. (2016)	
	Depth (mean)	average seabed depth (metres)	Letessier et al. (2019) and Tittensor et al. (2010)	GEBCO (2020)
	Feature proximity	Average distance to closest seamount or knoll feature (kilometres)	Letessier et al. (2019) and Tickler et al. (2017)	Yesson et al (2020, 2021)
Policy	Jurisdiction	classification of grid location (SL EEZ, high seas, or FEEZ)	Arias et al. (2015)	Derived from primary data
	Distance to FEEZ	distance from middle (centroid) of grid to closest FEEZ line (kilometres)	Kellner et al. (2007)	

models). We used deviance explained, effect size, *p*-values and findings from thematic analysis of qualitative data to interpret how well our models explained spatiotemporal effort.

2.8 | Investigating non-compliance

Exploratory analysis revealed the low predictability of non-compliance using statistical modelling, as a function of vessel characteristics (further details and table of results included in SD 5: Modelling non-compliance). Therefore, we opted for a descriptive multivariate analysis to identify the characteristics of non-compliance. Based primarily on insights generated through thematic analysis, we identified the following characteristics as potentially important in influencing non-compliance: vessel size, annual catch worth, reliance on income from sharks, annual vessel running costs, average distance travelled and non-compliance. PCA was used to identify key characteristics driving variance between vessels and provisionally identify clusters of vessels. Then, Hierarchical Cluster Analysis (HCA) was used to refine clusters. 'Ward's' method of agglomerative hierarchical clustering was chosen as it provided the strongest clustering structure (agglomerative coefficient of 0.95), and the elbow method was used to define optimal cluster number. All analysis was done using the FactormineR package (Lê et al., 2020) and visualised with factoextra package (Kassambara & Mundt, 2020).

3 | RESULTS

3.1 | Vessel and fisher characteristics

Overall, a total of 95 fishers completed both interview activities (50 in site 1 and 45 in site 2). Refusal rate was relatively high (~25%) mostly owing to the time demands of the survey. Fishers had, on average, 26 ± 10 years' experience, and all were reliant on fishing for 100% of their income, with 72% expressing they were satisfied, or extremely satisfied, with their income. Median vessel earnings were $78,175 per annum (interquartile range = $58,896). Sampling coverage was estimated, using national vessel registration data, as 25% and 22% of registered vessels in sites 1 and 2 respectively (National fisheries data, 2019). If we assume representative sampling, then earnings across both sites potentially total $35,746,445 per annum, from 8,597,120 fisher days at sea. Vessels exhibited a range of characteristics (Table 3), fishing behaviours and strategies (Figure S3), illustrating the multifarious nature of the fleet.

Median trip duration was 30 days and most vessels ($n = 85$, 89%) reported fishing outside the Sri Lankan EEZ. Ninety per cent ($n = 76$)

TABLE 3 Characteristics of sampled vessels (n = 95) extracted from interviews. **Mean**, standard deviation (±) and range (Ra=) are given. Average reliance on sharks is defined as the proportion of annual fishing effort that is expended for sharks

Vessel attribute	Sample fleet
Vessel Length	**12.5** ± 1.5 (Ra = 9.1–16.5) m
Crew size	**5.3** ± 0.8 (Ra = 4–7) pers.
Length of trip	**30.5** ± 14.4 (Ra = 4–77) days
Travelling time per trip	**9.6** ± 8.6 (Ra = 1–45) days
Number of trips (per annum)	**9.5** ± 6.2 (Ra = 2–45) trips per annum
High Seas Licence (HSL)	**87.4%**
Equipment (navigation and surveillance)	**41%** had both VMS & AIS **23%** had VMS only **7.5%** had AIS only **28.5%** had neither
Annual catch worth	**$88,362** ± 51,010 (Ra = $16,032–$238,500)
Annual fishing days	**224** ± 66 (Ra = 110–330)
Reliance on sharks	**6.6** ± 15.8% (Ra = 0%–100%)

of vessels that fished outside the EEZ held HSL, although 26% (n = 22) of them did not have the required working VMS. Vessels from site 2 travelled, on average, further than those from site 1 (1,011 and 875 km respectively).

A range of targeting strategies were reported, with 25 unique combinations of gear and species provided. Most common gears were long-line (n = 68, 71%) and gillnets (n = 53, 66%). Over half of vessels (n = 45, 51%) reported using a combination of both and 7.4% (n = 7) of vessels stated they had long-lines specifically adapted for targeting sharks. When asked to provide three target species in order of importance, fishers provided 15 unique target species assemblages. Tuna was the most common primary target species (n = 88, 94%), followed by Carangidae (e.g. Scads) (4%), billfish (e.g. swordfish; n = 1, 1%) and sharks (n = 1, 1%). Only 19% of fishers reported targeting sharks; however, 75% of fishers said that sharks contributed to their annual income (median contribution was 0.3%).

3.2 | Spatiotemporal distribution of fishing effort

Vessels targeted areas across the Northern, Southern and Western Indian Ocean (20.1°N to 12.4°S and 51.8°E to 89.8°E). Fishing effort was concentrated in the areas off SW Sri Lanka towards the Maldivian EEZ (Figure 2), although other notable hotspots included off NE Sri Lanka, the NE tip of the Maldivian EEZ and southern Indian EEZ. Overall, 53.9% was within high seas, 40.9% within the Sri Lankan EEZ and 5.2% in foreign waters (see Figure S4 for total fishing effort by country). Mapping indicated that vessels, on average, expended 7.2% of annual fishing effort within foreign waters, however a small subset of vessels (10%, n = 9) expended >25%. Effort was focused along borders (Figure 2a), which fishers explained was due to perceptions of higher catch quantity and worth in these areas. One fisher summarised '*our vessels stay close to borders targeting fish which are inside the borders. They wait until the fish come out with the water current*'.

Spatial distribution of effort varied as a function of target species, with fishers targeting sharks travelling 1,292 km on average, 50% further than those who did not (865 km). Hotspots of fishing effort for sharks were in distant waters (Figure 2b). Fishers explained that fishing trips for targeting sharks typically took longer due to the location of traditional sites, summarised by one fisher who said '*for a shark trip 60 days but for other 30 days*'. Low levels of effort for sharks were present across many areas, however, and fishers explained they are often caught incidentally due to non-selective gear types. Only 1% of vessels said that sharks were their primary target species, yet sharks provided income for fishers in 74% of the grids and represented 7% of the fleet's total annual income.

Fishers often said trip distances had become shorter over the last 10 years, owing to economic factors, including increased fuel price and declines in catch prices which had decreased the profitability of trips to distant waters. However, trip duration had reportedly increased due to a decrease in fish populations across all areas, especially within the Sri Lankan EEZ, meaning it was taking longer to fill catch holds.

3.3 | Spatial modelling

The best GLM model explained 36% of the deviance in spatiotemporal effort (adjusted R^2), with ~14% explained by social variables, ~11% by environmental variables and 12% by SAC (Table S3). The effect of individual variables is shown in Table 4. Distance to landing site, catch worth, SST and feature proximity all had a negative effect on fishing effort (Figure 3). Distance to sites explained the most deviance of the social variables (13%) and was an essential variable for all models (see Figure S5 for variable AIC weights). Fishers explained effort is lower in distant waters despite higher worth of catch due to higher fishing costs, for example '*in the areas far away, we earn high income, but the expenses are really high*'. Proportional effort for sharks significantly increased with distance from landing sites ($p < 0.001$). Similarly, policy variables, notably jurisdiction of the grid and distance to EEZ were both significant (both $p < 0.001$), suggesting they may affect spatial behaviour, but were not included in the final models. Vessel equipment also emerged as important from thematic analysis, as the absence of advanced cold storage (vessels are reliant on ice) purportedly influences fishing area choice. One fisher summarised '*it's because we have only a short distance to travel from here than to that place, so we can land the fish in fresh form*'.

3.4 | Non-compliance

During interviews, 26% (n = 25) of fishers said they had fished in foreign waters at some point in the last 5 years and 14% (n = 14) of fishers said they had done so in the last year. In contrast, 62% of fishers

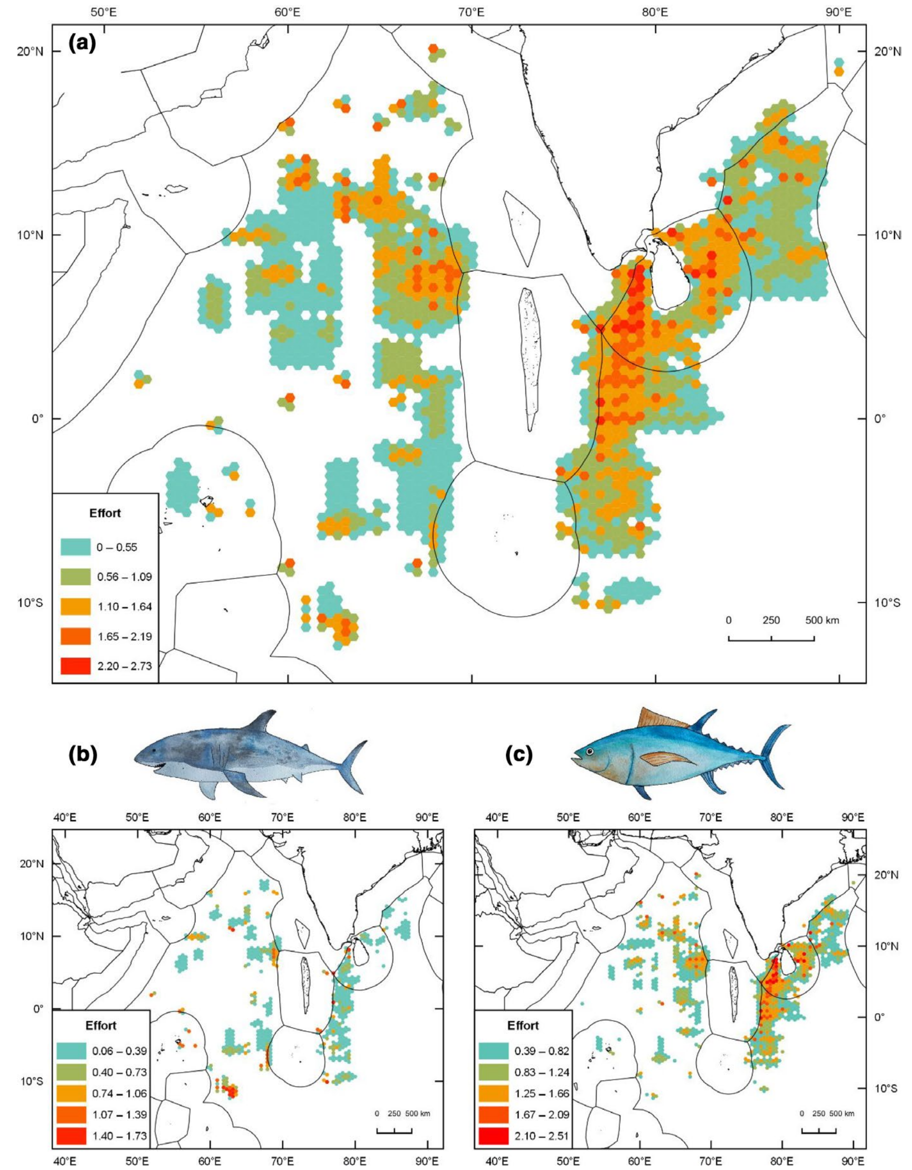

FIGURE 2 Distribution of fishing effort (LOG10[fishing days + 1]), for all vessels (a), Distribution of fishing effort (LOG10[fishing days + 1]), for sharks (b), Distribution of fishing effort (LOG10[fishing days + 1]), for tunas (c). EEZs indicated by black lines

mapped some (>0.1%) of their annual fishing effort within foreign waters. We compared our results with a previous study (Gunasekara & Rajapaksha, 2016) that used available data from VMS to map distribution of the same IMUL fleet. We found our data potentially indicate a higher level of non-compliance (Figure 4).

The analysis of qualitative data identified potential variables explaining non-compliance. Perceptions of higher catch were most frequently mentioned (58% of all surveyed fishers), followed by higher catches of sharks specifically (13% of surveyed fishers) and economic necessity (13% of surveyed fishers). The results of thematic coding to identify important variables explaining non-compliance are shown in Table 5.

3.5 | Characteristics of non-compliant vessels

PCA revealed 69% of the variability in the chosen characteristics of vessels was explained by the first (PCA1 = 52%) and second principal components (PCA2 = 17%) (Figure 5c). Four characteristics contributed almost equally to PCA1, including average catch worth (25%), average distance travelled (24%), average vessel running costs (24%) and size (21%) (Figure 5a). In contrast, non-compliance only contributed 0.1% to PCA1, but contributed the most (9%) to PCA2 (Figure 5b). Distribution of sampled vessels in relation to PCA1 and PCA2 is shown (Figure 5d), as well as the direction of effect for each characteristic.

HCA identified four homogenous clusters of fishers based on similar shared characteristics, with an agglomerative coefficient of 0.9, suggesting good cluster structure (see Figure S7 for HCA dendrogram). Most (78%) vessels were associated with clusters characterised by high compliance, with medium and low compliance associated with the smallest clusters (6% and 16% respectively). Clusters associated with medium and low compliance had highly variable associated characteristics, as shown in Table 6. Vessels that expended ~10% of their effort within foreign waters (not including India) were associated with high reliance on sharks (63.8%) and long distances travelled. Vessels that expended ~30% of their effort in

TABLE 4 Explanatory variables, effect on response (*p*), deviance explained for best GLM (De) and importance across all possible models (AICw)

Response	Category	Explanatory variable	*p*	De	AICw
Fishing days	Social	Distance to sites	<0.001	13%	1
		Shark reliance	<0.001	1%	0.9
		Catch worth	<0.001	>1%	0.9
	Environmental	Feature proximity	<0.01	>1%	0.9
		Depth	N.S	>1%	0.3
		SST (median)	<0.001	8%	1
		SST (sd)	<0.001	2%	1
		Chlorophyll (median)	<0.001	n/a	0.7
	Policy	Jurisdiction	<0.001	n/a	0.6
		Spatial autocorrelation (SAC)	<0.001	12%	1

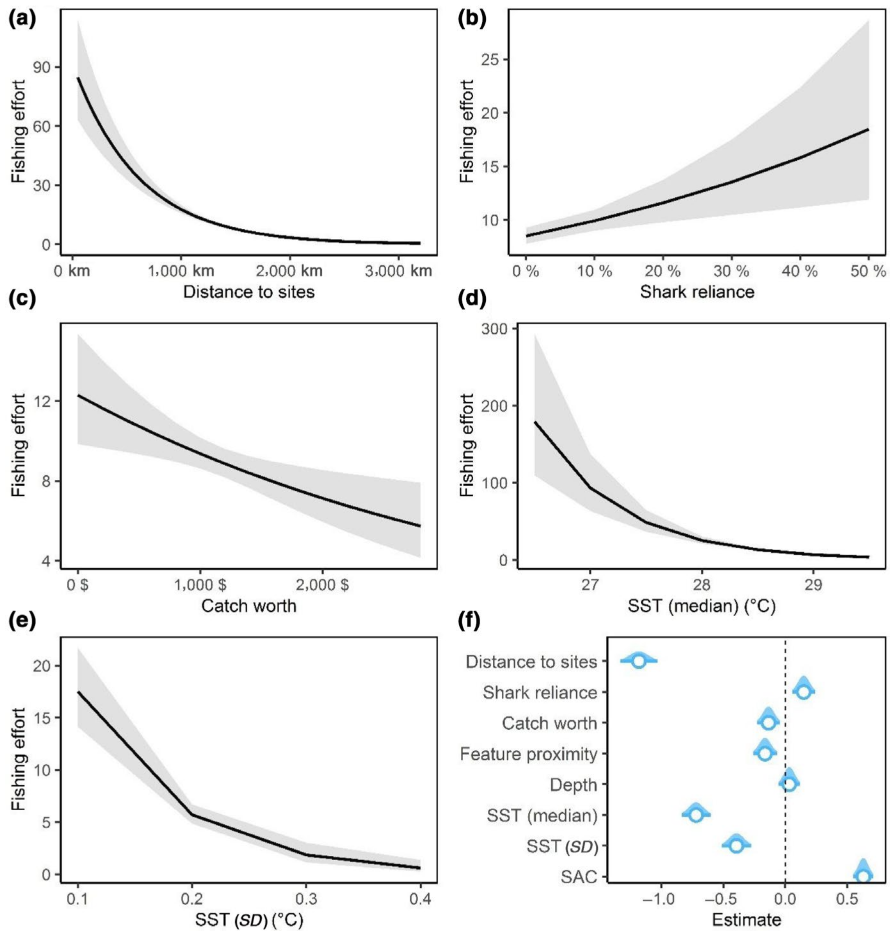

FIGURE 3 Partial effects of explanatory variables on fishing effort (days) in the model while considering the other variables are held constant. Relationships between fishing effort and distance to sites (a), shark reliance (b), catch worth (c), SST (median) (d) and SST (sd) (e). Coefficient effect estimates for all variables in the model are also shown (f)

foreign waters (including India) travelled shorter distances, earned less and were less reliant on sharks (~1.8%). Within cluster variance was high for characteristics, including non-compliance (Figure S8).

3.6 | Trends in non-compliance

Overall, there was a broad consensus that non-compliance had decreased, because of enhanced enforcement of FEEZs, national regulatory changes (including introduction of HSL) and widespread uptake of VMS (see Figure S9 for coverage of monitoring and surveillance equipment on sampled vessels). The analysis of interview data suggested that 24% of surveyed fishers had been arrested for fishing illegally in foreign waters at some point but only 8% of fishers had been arrested over the last 5 years. One fisher opined '*now the boats which go to other countries' waters are less as there is a higher possibility to get caught than before*'. With regard to VMS, one fisher said, '*now the technology is developed, and the thinking pattern of people also has*

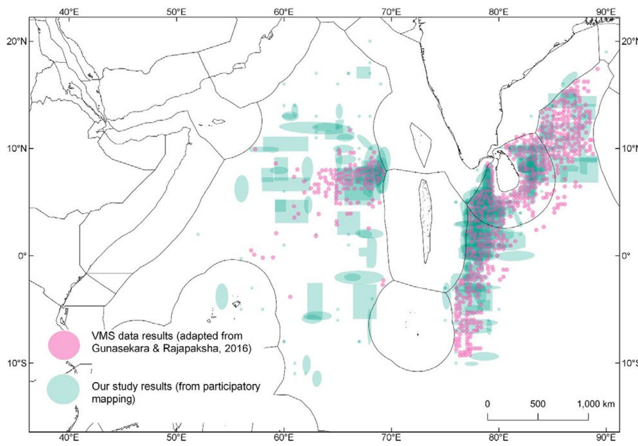

FIGURE 4 Comparison of identified fishing areas for the Sri Lankan IMUL fleet taken from our study results (highlighted in blue) and a report of VMS data adapted from Gunasekara and Rajapaksha (2016) (highlighted in pink). VMS data were taken from 1,311 boats, operating 3,275 trips, from January to April 2016

changed'. Interestingly, however, fishing effort in foreign waters was highest for vessels with VMS (8.5%), followed by vessels without either VMS or Automatic Identification System (AIS) (7.6%). Vessels with both VMS and AIS had the lower fishing effort in foreign waters (5.3%) (Figure S9). Advances in VMS were welcomed by many fishers, who explained this increased safety and decreased likelihood of accidental non-compliance. One fisher stated, '*fixing VMS is best because people know where they go. It's not favourable when it comes to profit but it's better than getting caught and suffering*'. Multiple fishers highlighted negative impacts of non-compliance, including long periods of unemployment, saying '*if I get caught, I have to suffer a lot as well as my entire family*'.

4 | DISCUSSION

The drivers of fishing effort distribution and compliance with spatial marine management policies are both critical research

TABLE 5 Potential variables explaining non-compliance identified from thematic analysis of qualitative data collected during interviews and participatory mapping with all surveyed fishers ($n = 95$)

Name of factor	Description	Evidence of importance	Illustrative quote(s)
Economic gains	Fishers explained that higher catch within FEEZs allows vessels to fill up quicker, spend less money on costs and return to landing sites quicker to prevent degradation of fish	• 58% of fishers mentioned higher catch as a primary factor • 14% said non-compliant vessels are pursuing higher profits than other (law-abiding) vessels. • Annual profits were $17,585 higher, on average, for vessels that expended >25% of effort in FEEZs	'*It's mainly because more fish could be obtained from those areas. Fish in Sri Lankan waters and even in international waters are very less now*'
Species-specific targeting behaviour	Fishers said vessels target sharks as they are high value, well-suited to vessel equipment and degrade slower. Perceptions of higher shark populations in FEEZs reportedly motivate vessels to target these areas	• 13% of fishers mentioned targeting of sharks as a primary factor • Fishers provided waypoints for targeting sharks that were within FEEZs • Contribution of sharks to annual catch worth was much higher (21%) than average (6.6%) for vessels that expended >25% of their fishing effort in FEEZs.	'*Most of the time they go to other countries to catch sharks*' '*There are some vessels who only go for sharks. They go to these areas and catch sharks*'.
Economic necessity	Fishers explained high running costs of larger vessels incentivise them to target FEEZs to recoup costs and repay debt	• 13% of fishers said high running costs of larger vessels were a primary factor	'*In these waters we don't have fish. Those big boats have lots of expenses, so they need big catch to recover costs*'
Perception of risk	Fishers explained that different perceptions of risk of capture may affect behaviours	• Differences in perception of risk among fishers were mentioned by 6% of fishers • Data highlight large disparity in perception of risk of capture, from 0% to 100%, average was 30.6% (± 34.3)	'*Very low chance of capture*' '*75%; those countries have good technology and can easily find out when we cross borders*'
Social norms	Fishers explained that perceptions of others engaging in activities may increase non-compliance	• Non-compliance was higher at site 1 than site 2 (56%: 44%) • Fishers that admitted non-compliance were more likely to think others also were (Figure S6)	'*We listen to the radio signals and when our friends tell that there is a good place to get a good catch, we sail to that place*'
Social network	Fishers explained that groups of vessels may engage in non-compliance in a coordinated manner, to engage in illegal activity	• 6% of fishers said groups of vessels, characterised by either owner or targeting strategy, engage in non-compliance	'*There is a specific group who mainly target sharks. There is one company all of his boats go there only*'

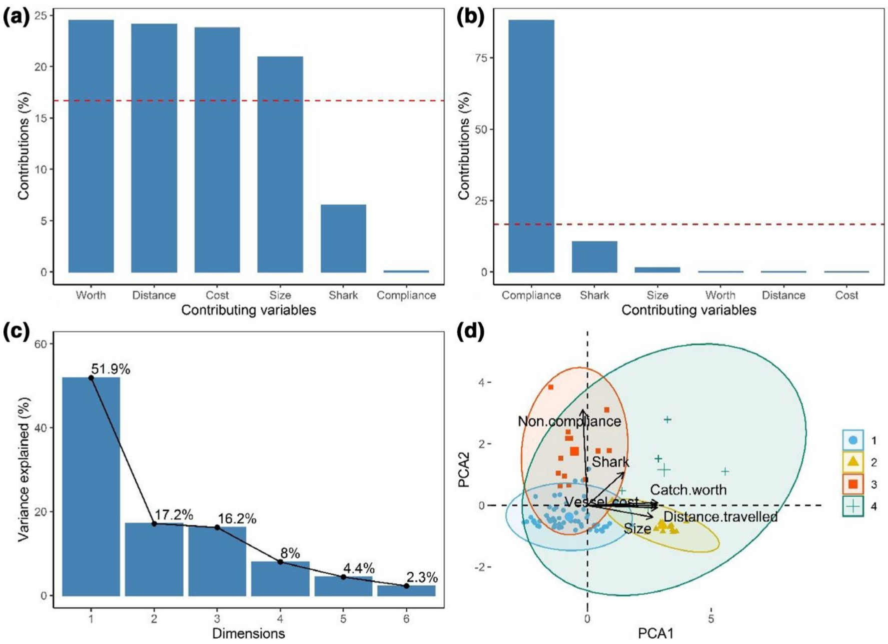

FIGURE 5 Principal component analysis of vessel characteristics. Contribution of variables to PCA1 (a) and PCA2 (b), scree plot showing variance explained by each dimensions (C), biplot demonstrating the direction of effects of variables on PCA1 and PCA2 (d), with vessel clusters (group 1–4), identified by Hierarchical Cluster Analysis, highlighted by ellipses with a 95% confidence interval. Mean points of groups (barycentres) are shown as larger symbols

TABLE 6 Group centroids (mean scores) and descriptions for the four clusters identified by HCA

Cluster description	Self-reported non-compliance	Shark reliance	Catch worth	Vessel costs	Size	Distance	Other
Group 1 **High compliance** **63% of vessels/54** Small vessels, travelling short distances, low catch earnings, low reliance on sharks	2.9%	3.5%	$66,205	$23,769	12.1	746	Site 1:34 Site 2:
Group 2 **High compliance** **15% of vessels/13** Large vessels, travelling medium distances, high catch earnings, low reliance on sharks	1.4%	4%	$170,925	$73,405	14.4	1742	Site 1:1 Site 2:10
Group 3 **Low compliance** **16% of vessels/14** Small vessels, travelling short distances, low-medium catch earnings, low reliance on sharks	29.2%	1.8%	$86,227	$33,237	11.9	712	Site 1:5 Site 2:8 Fishing in Indian EEZ = 18.8%
Group 4 **Moderate compliance** **6% of vessels/5** Large vessels, travelling long distances, medium-high catch earnings, high reliance on sharks	9.4%	63.8%	$138,595	$43,857	14	2,137	All site 1 Fishing in Indian EEZ = 0%

and management aspects (Battista et al., 2018; McCluskey & Lewison, 2008; Oyanedel et al., 2020). We examined these issues for a highly mobile fishing fleet suspected of historical and ongoing non-compliance. Our approach is novel, and our findings highlight the importance of continued advancements in monitoring and management of fleets. Further, our results show how participatory and social data can produce nuanced, detailed understanding of fleet movements, which may be omitted by relying on VMS alone.

4.1 | Spatiotemporal effort distribution

Our results re-emphasise that fisheries effort is related to both social and environmental dimensions (McCluskey & Lewison, 2008). Distance to landing site, previously highlighted as influential of fish population status at the scale of the EEZ (Letessier et al., 2019; Maire et al., 2016), emerged as the most important social variable. This has previously been identified as an important factor in fisher decision-making within coastal regions (Cabanellas-Reboredo et al., 2014) but, to our knowledge, has not been documented as an important driver of fleet behaviour on the high seas (Kroodsma et al., 2018). Both catch worth and proportional reliance on sharks also emerged as important social variables, emphasising the importance of economics in driving effort. The economic profitability of fishing in high seas areas is highly variable among fishing fleets, dependent on factors such as fuel price and catch worth (Sala et al., 2018), and spatial distribution of this fleet is likely to be affected by future changes in either. We investigated the role of spatial management policies on fleet behaviour, and found it had a significant effect, confirming the role of political boundaries in fisher decision-making. Overall, the patterns of effort distribution were generally consistent with the reports from VMS (Gunasekara & Rajapaksha, 2016). However, our study approach adds understanding of non-compliant effort, showing a complementary and more nuanced picture.

4.2 | Non-compliance

We provide detailed empirical evidence of non-compliance for this fleet, the occurrence of which has previously been documented by enforcement records (Martin et al., 2013), shark telemetry research (Tickler et al., 2019) and social studies (Amarasinghe, 2003, 2013). The findings of non-compliance contrast with previous studies that used VMS data to show the fleet was broadly compliant (Gunasekara & Rajapaksha, 2016). We suggest VMS may only provide partial coverage due to incomplete uptake and fishers actively turning it off. Heterogeneity in compliance levels within the fleet was evident and qualitative data identified potential decreases in non-compliance during the study period. We highlight that the bulk of non-compliance was conducted by a small, active minority, but likely had negative implications for all resource users and effectiveness of spatial management policies, such as MPAs, within the region (Arias et al., 2015).

Our research explored potential motivations for non-compliance, which are highly context specific (Petrossian, 2015). Perceptions of economic gains, when expected benefits exceed cost of non-compliance, are important (González-Andrés et al., 2020; Le Gallic & Cox, 2006) and we identified an association between non-compliance and desire to increase earnings. This was moderated by other economic factors previously identified as important, notably overcapacity and overfishing in traditional fishing areas (Sumaila et al., 2006). Perceived economic gains from illegal fishing are moderated by perception of risk of capture (Sumaila et al., 2006) and we observed highly variable perception of risk among fishers and evidence that this was linked to non-compliance likelihood. We also found evidence that targeting of sharks is associated with non-compliance, supporting research linking high populations of species viewed as valuable in marine areas to non-compliance (Carr et al., 2013; González-Andrés et al., 2020; Petrossian, 2015; Raemaekers et al., 2011). This has important management implications and highlights the importance of understanding social drivers for shark fisheries when considering compliance (Collins et al., 2020). The role of social norms (the behaviour of others and what they approve of) on compliance is increasingly acknowledged and studied (Battista et al., 2018; Hatcher et al., 2000). Our thematic analysis results suggest that interpersonal and community links within the Sri Lankan fleet may be an important factor to consider for management of non-compliance.

4.3 | Management insights

Our study highlights the potential of participatory data for understanding and managing species-specific effort distribution of highly mobile fishing fleets (McCluskey & Lewison, 2008). We demonstrate frequent interaction with vulnerable non-target species, such as sharks, across the fishing range (Dulvy et al., 2008; Worm et al., 2013). Sharks are increasingly protected across their Indian Ocean ranges, including bans on exploitation in the Maldives and BIOT. However, there is an identified need to refine and better enforce the spatial protection of population refuges (Letessier et al., 2019). We demonstrate how participatory data can incorporate fisher knowledge on population distribution and highlight biological hotspots. Accordingly, we advocate for further discussion of how spatial management policies can increase protection afforded to sharks.

Based on our study results, we advocate for increased data sharing regarding non-compliance across this region and, at a national level, an investigation of factors limiting the uptake of VMS to address partial monitoring of this fleet. Overall, however, our findings highlight that individual decisions to engage in non-compliance are highly context specific (Arias et al., 2015) and management interventions should be adapted to these local contexts (Petrossian, 2015). We suggest increases in localised, targeted interventions designed with specific vessel characteristics or variables in mind. For example, further study of the importance of social network connections among non-compliant vessels for coordination of non-compliant activities, which fishers suggested, may be an important motivating factor.

4.4 | Study limitations

In this study, we identify shortcomings in using vessel tracking technologies alone to understand fleet behaviour and highlight the complementary use of participatory and social data (Thiault et al., 2017). However, our results should be interpreted in context. Firstly, it is unclear as to what extent they are representative of the whole Sri Lankan fleet, as we chose to sample two sites only. In addition, our model had relatively low explanatory power, indicating that other important variables may be important to consider. For example, seasonality is identified as a key driver of fleet behaviour across scales (from small-scale fisheries to large-scale industrial fleets) (Béné & Tewfik, 2001; Guiet et al., 2019; Pérez-Jiménez & Mendez-Loeza, 2015). However, the bulk of effort reported by fishers for this study was not seasonally resolved and therefore could not be retained for further consideration. Other factors identified as potentially important during thematic analysis, but not included in spatial modelling, include the influence of social networks and traditional fishing patterns. In order to further resolve the explanatory power of our models, further analysis on subsections of the fleet, and over shorter time frames, may better capture seasonality and the influence of social networks.

Our findings regarding non-compliance should also be considered in context. Mapping produced higher estimates of non-compliance than Direct Questioning (DQ). DQ has been associated with introduction of bias when addressing sensitive topics (Solomon et al., 2015), particularly when relationships with participants are not established (Mann, 1995). Accordingly, we identified no-response bias and response bias within our study, as participation was refused by fishers and some admitted concealing non-compliant behaviour. Efforts were taken to eliminate these records, resulting in deletion of five participants' data; however, we advocate for further research into non-compliance using specialised methods, such as unmatched-count techniques (Nuno & St. John, 2015). This would help to establish potential effects of identified variables on non-compliance, and strengthen management recommendations (McCluskey & Lewison, 2008).

5 | CONCLUSION

Our study has two main important policy implications. Firstly, our results highlight the importance of integrating social dimensions into understanding of spatial behaviour of high seas fleets and predicting and managing non-compliance with spatial management policies (Arias et al., 2015; Fulton et al., 2011; Pons et al., 2018). Secondly, we highlight that monitoring of high seas fleets using vessel tracking technologies alone may create an incomplete picture. We show the potential value of complementary approaches, such as collection of participatory data, to build a complete understanding of illegal fishing. We advocate for more nuanced approaches to combatting non-compliance across scales (Österblom et al., 2011), including local-level interventions.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHORS' CONTRIBUTIONS

C.C., A.N. and T.B.L. conceived the ideas and designed the methodology, with inputs from I.W., D.W. and A.B. to adapt the methodology for the local contexts; I.W., D.W. and A.B. collected and translated the data; C.C. analysed the data and led the writing of the manuscript. All the authors contributed critically to the drafts and gave final approval for publication. C.C. is the first author, T.B.L. is the last author (primarily responsible for supervising all manuscript processes) and A.N. is the second author (responsible for substantial contributions to methodology, review and editing). All other authors are given in alphabetical order.

DATA AVAILABILITY STATEMENT

Data are available at the Dryad Digital Repository https://doi.org/10.5061/dryad.qjq2bvqg4 (Collins et al., 2021).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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