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Using vessel surveillance data to estimate spatiotemporal patterns in the short mackerel purse-seine fishery: implications for time–area closure management in Thai waters

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Highlights

- Timely and accurate information is required to manage heavily exploited migratory fish species
- VMS and landing data can provide reliable information on fishing effort and fish abundance
- Spatiotemporal adjustments in fishing effort for short mackerel followed closures
- So-called derby fishing and ‘fishing in line’ by vessels were observed during seasonal closures
- Fishery closures should be revised in response to fish population fluctuations

ABSTRACT

Mapping fishing effort and fish abundance across management areas is required to adjust and enforce time–area management measures. Seasonal closures are imposed in Thai waters to mitigate the overexploitation of short mackerel (*Rastrelliger brachysoma*), one of Southeast Asia's most economically important pelagic species. This study applied machine learning to fishing vessel surveillance data to estimate spatiotemporal distributions of fishing effort and fish abundance in the Gulf of Thailand (GOT) and the Andaman Sea (ADS) to provide reliable and near real-time information to support seasonal closures. Data collected between 2018 and 2020 from Thai purse seiners targeting short mackerel included VMS data, fishing trip records, and landing information. Spatiotemporal patterns in fishing effort and catch per unit effort (CPUE) were then visualized in relation to the closures in different statistical management zones. The results show that fishing effort in the ADS increased in 2020 from 2018 and 2019, and peaked in 2019 in the GOT. No significant spatiotemporal trend in the distribution of CPUE was identified over the 3 years. Notably, the results reveal spatiotemporal adjustments to fishing effort and CPUE following the implementation of seasonal closures. This study is the first to present a practical approach to using vessel surveillance data to examine seasonal patterns in fishing effort and estimated fish distribution in Thai waters. The findings improve our understanding of fishing effort in response to area closures. The information generated here supports the time–area management of an intensively exploited migratory fish species, given timely and accurate information.

Keywords: Fishing effort, Purse seiners, Seasonal closure, Spatiotemporal distribution, Vessel Monitoring Systems

1. Introduction

Spatial management of fisheries, such as implementing time–area closures, is crucial for enhancing overall fish production, restoring depleted fish stocks, and safeguarding habitats. Through area closures and effort restrictions, it is possible to reduce fishing mortality on both target and non-target species throughout critical life phases, in vulnerable habitats or with slower migration rates [1,2]. This approach also helps to maintain habitats and rebuild depleted fisheries [3–5], helps to optimize fleet capacity, and mitigates overexploitation of fish stocks when other methods of fisheries management are impracticable [3,6].

To evaluate the success of area-based fisheries management, detailed and recent spatial and quantitative information about the locations and extent of the fishing activities is required [7]. Mapping dynamic patterns of fishing effort across management areas remains an ongoing challenge for managing and enforcing spatial management measures [8].

Successful time–area restrictions rely on well-designed protected areas that accurately reflect the habitats of the target species in terms of their locations and extent [6,7,9]. Managing fishing mortality at smaller scales can lead to more effective control of a fishery due to fish quantity and distribution exhibiting higher spatiotemporal fluctuation. Conventional fixed-area closures do not adapt well to shifts in species distributions or changes in fishing effort, especially in the case of migratory species [10,11]. To establish and assess spatial management strategies and ensure their effective design and performance, it is imperative to evaluate the spatiotemporal distributions of both the fishing operations and the fish stock [1].

Collating data on fishing activity is invaluable for fisheries management, such as for identifying fishing locations, improving stock assessments, estimating fishing effort, and evaluating the impacts of exclusion measures [12]. The main data sources for estimating the spatial and temporal distributions of exploited fish stocks are scientific surveys and commercial fishing operations. However, since scientific surveys are typically conducted only once a year, their coverage is insufficient to capture seasonal trends. In contrast, although commercial fishing data may lack the geographic and temporal resolution of scientific data, commercial fishing records can reveal broad spatial and seasonal patterns [13].

A vessel monitoring system (VMS) is a tracking device installed on each fishing vessel that consistently transmits data on the vessel's position, speed, and heading to land-control stations via satellite transmission. This information provides important spatiotemporal datasets that are useful for

fisheries scientists to evaluate finer-scale spatial and temporal aspects of commercial fisheries [14]. The high-resolution vessel position data received by VMS allows for studies of the distribution of fishing effort and species-specific catch per unit effort (CPUE) when integrated with commercial logbook data. The VMS can determine the fishing operation's position, while the fishing logbook records each vessel's daily catch. For each vessel and date, the VMS recordings correspond to fishing activity for each vessel on a given date, and the catches can be distributed across all fishing areas for each vessel on each day [14,15]. This integration enables managers to monitor fishing efforts, detect changes in exploitation patterns, and gain insight into the spatial distribution of a stock. VMS data can also be used to identify fishing grounds and to quantify the impact of spatial management measures on the stock [16].

The short mackerel *Rastrelliger brachysoma* (Bleeker, 1851) is a migratory fish found in the tropical central-west Indo-Pacific region, from the Andaman Sea to Oceania [17,18]. Because of its high nutritional value and appealing taste, this species has high value in the commercial sector, particularly in Southeast Asia, including Thailand. Purse seines are the typical capture gear for this species, which aggregates in schools [17]. In Thai waters, purse seines are the primary fishing method for short mackerel, accounting for 65% of the catch, followed by paired trawls (22.9%) and gillnets (9.1%) [19]. An evaluation by the Southeast Asian Fisheries Development Center (SEAFDEC) carried out in 2019 indicated a significant decline in short mackerel catches in Southeast Asia during the previous decade [20]. Consequently, seasonal closures emerged as a prominent management strategy aimed especially at protecting spawning grounds and reducing short mackerel catches.

Thailand has imposed seasonal closures to safeguard mackerel spawning areas since 2018 regarding the new fisheries law (The Royal Ordinance on Fisheries B.C. 2558 (2015)), and the Department of Fisheries (DOF) has conducted various assessments of the species, such as stock status evaluations [21], and monitors the short mackerel life cycle by sampling catches from commercial fishing vessels. Kongseng et al. [22] emphasize the importance of ongoing monitoring of the short mackerel resource to support sustainable fisheries, particularly in the Gulf of Thailand (GOT). Recent research efforts have focused on defining the stock structure and studying the species' population genetics. Two distinct sources of fully mature mackerel captured were identified by the genomic investigation. A particular population resides in the inner GOT and remains stationary, while another group, which migrated from the South GOT, remains stranded in the Eastern GOT [22,23]. Moreover,

Thailand's DOF first employed physical tagging of short mackerel in 1963 to study its migration patterns in the GOT [24].

Nevertheless, in the context of some outdated information and recent environmental changes, the distribution of short mackerel across the entire national jurisdiction merits reevaluation. Analyzing data from year-round commercial fishing vessels will improve our understanding of the seasonal distribution of this stock. Additionally, no research on quantifying changes in fleet effort, which is a proxy for changes in fishing mortality following the implementation of seasonal closures. Addressing these knowledge gaps can contribute to more effective management planning and promote sustainable fishing practices for this migratory species.

This research aimed to provide valuable information on seasonal closures in the GOT and Andaman Sea (ADS) by investigating the spatiotemporal distributions of fishing activity and fish abundance. First, our analysis was directed at uncovering the overall spatiotemporal characteristics of the fishing effort and fish distribution. Next, we analyzed whether commercial fishing activities had changed in response to the seasonal closures implemented in the GOT and ADS based on data from 2018 to 2020. Since purse seining is a commonly employed method for capturing short mackerel, which forms large schools, positioning data from commercial purse seiners obtained through VMS, plus landing information from each fishing trip, were used to estimate spatiotemporal patterns in the stock distribution and abundance.

2. Materials and methods

2.1. Study area and management measures for short mackerel

The study area comprised the GOT and ADS, which are both important fishing grounds in the short mackerel fishery (Fig. 1). Purse seiners are the primary gear employed to capture schools of short mackerel. The vessels usually install echo sounders and operate with fish aggregating devices and light luring vessels for fish attraction. To protect the spawning and nursery grounds of short mackerel, Thailand has introduced seasonal closures. During the study period, four seasonal closures among five fisheries statistical zones in the GOT and one closure among two fisheries statistical zones in the ADS were enforced yearly (Fig. 1). Figure 1 describes the annual implementation of one closure in ADS and four seasonal closures in each of the five GOT zones.

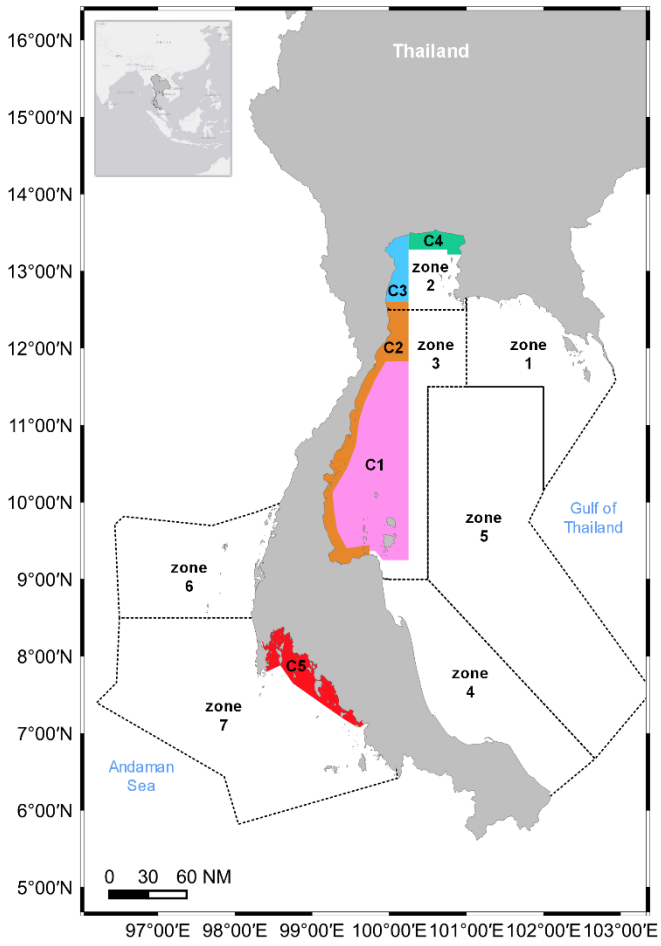


Fig. 1. The Gulf of Thailand (GOT) and the Andaman Sea (ADS) are the two distinct fishing grounds governed by separate management areas in Thailand. The fisheries statistical zone has been divided into 7 zones: zone 1 in the Eastern GOT, zone 2 in the Upper GOT, zone 3 in the Western GOT, zone 4 in the Southern GOT, zone 5 in the Middle GOT, zone 6 in the Upper ADS, and zone 7 in the Lower ADS. Five seasonal closures have been implemented every year: the first closure (C1) in the middle GOT from 15 February to 15 May; the second closure (C2) in the upper to middle GOT from 16 May to 14 June; the third closure (C3) in the upper GOT from 15 June to 15 August; and the fourth closure (C4) in the upper GOT from 1 August to 30 September. A single closure (C5) occurs near the coast in zone 7 of ADS from 1 April to 30 June (Fig. 1).

2.2. Data sources

Thailand's DOF provided VMS data from purse seiners that landed short mackerel in the GOT (382 vessels) and in the ADS (109 vessels) from 2018 to 2020. The initial VMS data consisted of approximately 12,903,480 records, with the vessel positions recorded (latitude, longitude), date, and

time continuously at 1-h intervals. The operations must be identified before using the vessel position data, as the VMS fails to indicate the fishing activity while transmitting it.

Electronic information on fishing trips that specifically targeted short mackerel was also collected for the 3-year study period: 24,322 fishing trips in the GOT and 6,329 fishing trips in the ADS. Fishing trip records were paired with the VMS data to verify that the data were obtained and limited to trips to fish that caught short mackerel. To ensure confidentiality in our handling of the VMS data, fishing trip identification was matched with VMS data using date, time, and vessel identification, with the assistance of authorities in the Department of Fisheries. After the matching process, the total number of recorded VMS data entries was approximately 1,780,461.

By utilizing fishing trip numbers, the VMS data was combined with the short mackerel landing data, which included the actual catch weight by species after weighing at the landing location of each trip for each vessel. For the purpose of allocating the catch to the fishing operation position in 2.3.2, this integrated information was created.

Paper-based fishing logbooks of commercial purse seiners were collected and classified as either fishing or non-fishing operations. In the logbook, each fishing trip skipper records the fishing activities while at sea, with each recorded row representing a fishing operation, including the date and time at the start of fishing operations (when the net was deployed into the sea). The fishing operation period (the start of pulling the net into the water until the entire catch is hauled out and collected) is defined in hours. After classification, the fishing activities were labelled in VMS data using date and time referring to vessel identification and fishing trip records to provide a training dataset. These datasets were utilized to train the predictive model using the supervised machine-learning approach (see the detail in 2.3.1) developed by Meeanan et al. [25]. A total of 26,300 records (970 fishing trips) in the GOT and 16,857 records (654 fishing trips) in the ADS were labelled and included in the training dataset due to the paper-based format of the fishing logbook data. It is challenging to compile every fishing activity from paper records covering three years. Furthermore, occasionally, the information on the document is not written correctly. The only logbook that was fully gathered and made accessible was utilized as a label in the VMS data in order to train the model and create a predictive model that would identify the positions of fishing operations. Since the remaining VMS data was not identified as a fishing operation according to the fishing logbook, it was regarded as unknown new input data. The unknown input data

will be able to classify the fishing operation positions when the predictive model is developed (see 2.3.1).

Records of sea surface temperature (SST, °C) and chlorophyll-*a* concentration (mg/m^3) at 8-day intervals, with a 4-km resolution, were obtained from MODIS Aqua and MODIS Terra (NASA's Goddard Space Flight Center, https://oceancolor.gsfc.nasa.gov). Sea depth (m) of a spatial resolution of 15 arc-seconds (~0.004°) was obtained from the British Oceanographic Data Centre, National Oceanography Centre (https://www.gebco.net). These environmental data were extracted with 0.03° resolution using the Raster package in R in preparation for machine learning to generate predictors or independent variables as the measurable and analyzable features of an object [26].

Data sources were integrated into a single dataset using date, time, and vessel position (latitude, longitude) as connecting components. All the data collected were used to generate the necessary predictors (Table 1) and apply a machine-learning approach to detect fishing operations and predict the distribution of short mackerel.

Table 1 Predictors for forecasting potential fishing operations and fish distributions in the Gulf of Thailand and the Andaman Sea using machine learning

Predictor name	Description
Temporal and fisheries-related predictors of fishing operations	
1. Date	The number of days in a given month ranges from 1 to 31
2. Day of the year	The date within a calendar year, containing a range from 1 to 366
3. Month	The months of the year range from 1 to 12
4. Hour	An equal number of 24 hours within a single day
5. Operation time (day or night)	Designating the times at 6 a.m. and 6 p.m. as indicators for sunrise and sunset, respectively, divides the transition between day and night.
6. Vessel speed	Instantaneous vessel speed determined by VMS data (knots)
7. $\Delta Speed_{curr-1}$	The different vessel speeds determined using the current and prior VMS records.
8. $\Delta Speed_{curr+1}$	The different vessel speeds calculated using the current and subsequent VMS records

Predictor name	Description
Temporal and fisheries-related predictors of fishing operations	
9. Standard deviation speed	The calculation of the standard deviation for the vessel's present speeds in the forward and reverse directions
10. Average speed	The calculation of the average for the vessel's present speeds in the forward and reverse directions
11. Calculated speed	The measurement of the distance between two consecutive locations (km)
12. ΔCalculated speed$_{curr-1}$	The different distances computed by the present and prior VMS records
13. Standard deviation of calculated speed	The standard deviation of the present distances in forward and reverse directions of calculated speed
14. Average of calculated speed	The average of the present distances in forward and reverse directions of calculated speed
15. Vessel size	Size of the registered vessel (gross tonnage)
16. Vessel length	Length of the registered vessel (m)
17. Fishing day	Duration of fishing trip (day)
18. Ratio of short mackerel catch to total landings	The ratio of short mackerel landings to the overall landings
19. Total short mackerel landing	Landings of short mackerel during a fishing trip
Spatial and environmental predictors for predicting fish distribution	
1. Distance from shore	Distance in km from the closest country line
2. Latitude	The determination of latitude using VMS tracking
3. Longitude	The determination of longitude using VMS tracking
4. SST	Eight-day sea surface temperature (SST, °C), with a 4-km resolution
5. Chlorophyll-*a*	Eight-day chlorophyll-*a* concentration, with a 4-km resolution
6. Sea depth	Sea depth (m) with a 15-arc-second (or 0.004°) spatial resolution

204

205

206 *2.3. Data analysis*

207 Three steps were followed to discern the characteristics of the fishing effort and fish distribution
208 across the year and among seasons, as well as any spatiotemporal patterns in response to seasonal
209 closures:

210 Step 1 – Identify fishing operations based on the surveillance data using the random forest (RF)
211 algorithm.

212 Step 2 – Allocate catch data to specific fishing operation positions.

213 Step 3 – Examine spatiotemporal characteristics of the fishing effort and fish distribution in
214 response to seasonal closure.

215 *2.3.1. Identifying fishing operations using the random forest (RF) algorithm*

216 The RF algorithmwas applied to identify the fishing operations ('fishing' or 'non-fishing') of purse
217 seine vessels, following Meeanan et al. [25]. RF requires the availability of labelled data, referred to as
218 the training dataset. In the fishing operation context, the data are often labelled as either 'fishing' or
219 'non-fishing' based on information recorded in the fishing logbook. The RF algorithm uses this labelled
220 training dataset to train and create a predictive model, which can then be used to classify the fishing
221 operation of unknown data. Owing to the possibility of operational differences between the two fishing
222 grounds and the spatial predictors, particularly latitude and longitude, two predictive models, one for
223 determining the fishing operation of the purse seiner operating in the GOT and the other for the ADS,
224 were created separately in this step. Accordingly, the training datasets for the GOT (26,300 records)
225 and the ADS (16,875 records) each received the labelled data (fishing vs non-fishing) from the fishing
226 logbook. To identify fishing operations that refer to the fishing effort, 19 variables were employed and
227 divided into temporal and fishery predictors (Table 1). The RF was performed using the package scikit-
228 learn, a Python module for machine learning [27,28].

229 In order to evaluate the performance of the models and prevent overfitting, the average
230 accuracy score was calculated using 10-fold cross-validation [29]. The confusion matrix was used to
231 summarize the area under the receiver-operating characteristic (AUROC). The AUROC was calculated
232 to summarize the sensitivity and specificity of the model. This evaluation was performed using the
233 confusion matrix data obtained from an 80% training set and a 20% testing set [4,30–32].

234

2.3.2. Allocating catch data to the fishing operation position

Random forest regression (RFR) was used to create a predictive model using six spatial and environmental predictors (Table 1) to estimate the catch. The dependent variable was the 'catch portion' of each fishing position calculated by proportioning the catch rate obtained from a fishing logbook's estimations and multiplied by the aggregate of the short mackerel landings throughout the current trip, following the approach and equation of Meeanan et al. [25].

The performance of the RFR model was assessed using the root-mean-square error (RMSE) and negative mean absolute error (MAE). To predict the estimated catch, the previously determined fishing positions (see section 2.3.1) were utilized as new input data and applied to the established RFR predictive model. Subsequently, the RFR estimated catch, indicating the probability of occurrence at each location, was normalized proportionally with the recorded short mackerel landings. The normalized catch values were then allocated to the predicted fishing positions using the formula:

$$R_{ik} = L_k \left[\frac{D_{ik}}{D_k}\right]$$

where R_{ik} denotes the reallocated catch in predicted fishing operation i of trip k; L_k is the total short mackerel landing of trip k; D_{ik} represents the estimated catch generated from RFR applied to fishing position i of trip k; and D_k describes the total of the estimated catch derived from the RFR of trip k.

2.3.3. Spatiotemporal structure of the fishing effort and fish distribution in response to seasonal closure

In order to describe a bimonthly pattern of fishing effort over time, the fishing operations targeting short mackerel (see section 2.3.1) were displayed on grids of 0.1° latitude × 0.1° longitude. Counting the number of predicted fishing positions within a grid was used to determine fishing effort. Since the interval between the VMS signal transmissions is 1 h, it was assumed that each position represented 1 h of fishing effort.

To show the shifting pattern of seasonal closures, the boundaries of each closure area were illustrated on a map of fishing effort distribution. The fishing efforts were classified by management area, consisting of five zones in the GOT and two zones in the ADS (Fig. 1), displayed on a monthly time scale. The formula for calculating the fishing effort E of 0.1° × 0.1° grid c and bimonthly t, is as follows:

$$E_{c,t} = \sum_{i=0}^{n} P_i$$

where P_i is the fishing operation of position i.

CPUE (kg day^{-1}) was calculated from the fishing effort (see section 2.3.1) and estimated catch (see section 2.3.2) and was then displayed bimonthly on the map at the same grid size as the fishing effort. Calculation of the CPUE of 0.1° × 0.1° grid c and bimonthly t follows the formula:

$$CPUE_{c,t} = \frac{\sum_{i=0}^{n} Y_i}{\sum_{i=0}^{n} P_i / 24}$$

where Y_i is the estimated catch of each fishing position i, and P_i is the fishing operation of position i. The CPUE was also split by fisheries management areas (i.e., GOT and ADS) and depicted as a monthly dimension. The metrics were calculated to introduce a new method of using preexisting VMS as surveillance data rather than relying on calculations based on departure and return times obtained from fishermen's interviews and trip records. This method utilizes the exact duration of net deployment from VMS data. To standardize the units, fishing hours were converted into days by dividing by 24. The CPUE data continues to offer insights into abundance levels. Regarding the identification of fishing activity locations obtained from the VMS can potentially be determined with greater precision, thereby enhancing the resolution of abundance sources.

3. Results

3.1. Spatiotemporal patterns in fishing effort

3.1.1. Model performance in detecting fishing effort

The RF model showed an average accuracy of 83.15% and 83.82% for identifying fishing operations in the GOT and the ADS, respectively, with a standard deviation of 2.58% and 1.73%. The AUROC values were 94.40% and 93.40%, respectively.

3.1.2. Spatiotemporal distribution of fishing effort

The fishing effort observed in the GOT is depicted in Fig. 2. For 2018, 2019, and 2020, the total numbers of VMS locations extracted hourly, indicating fishing effort, were 84,354 h, 124,031 h, and 110,789 h, respectively. The levels of fishing effort in 2019 and 2020 were approximately 47.03% and 31.33% higher, respectively, compared with that in 2018. Fishing effort was concentrated near the shoreline, which could be divided into three main areas: the upper GOT (management zone 2), the middle GOT (management zone 3), and the lower GOT (management zones 4 and 5). Throughout the year, the distribution of the fishing fleet within zones 4 and 5 (the lower GOT) remained relatively stable, while the fleet's distribution in zones 2 and 3 exhibited fluctuations over time. In 2018 and 2019, the

fishing effort peaked in July and continued gradually to increase until October. However, in 2020, the fishing effort began to increase earlier, in May and persisted through August.

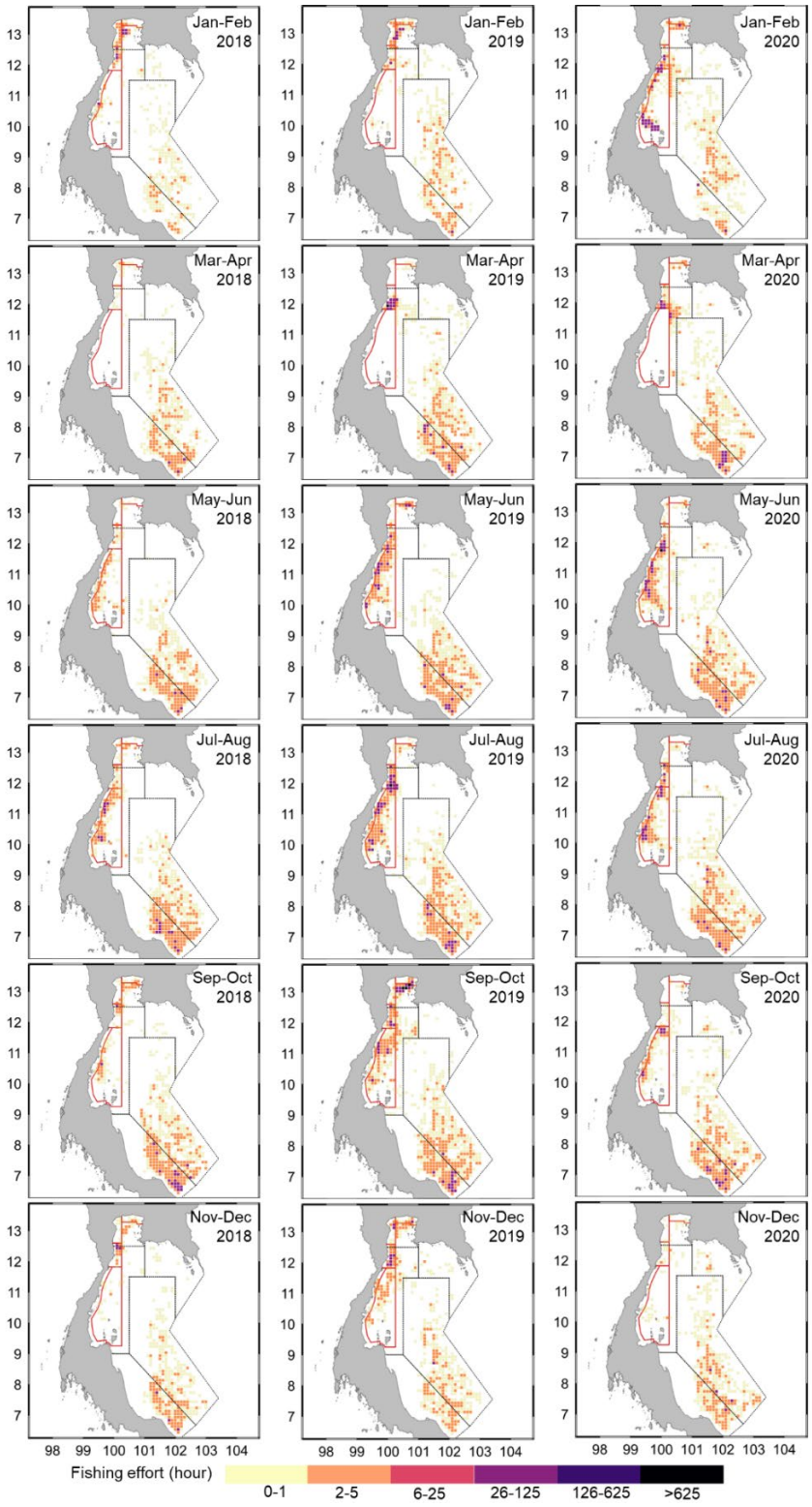
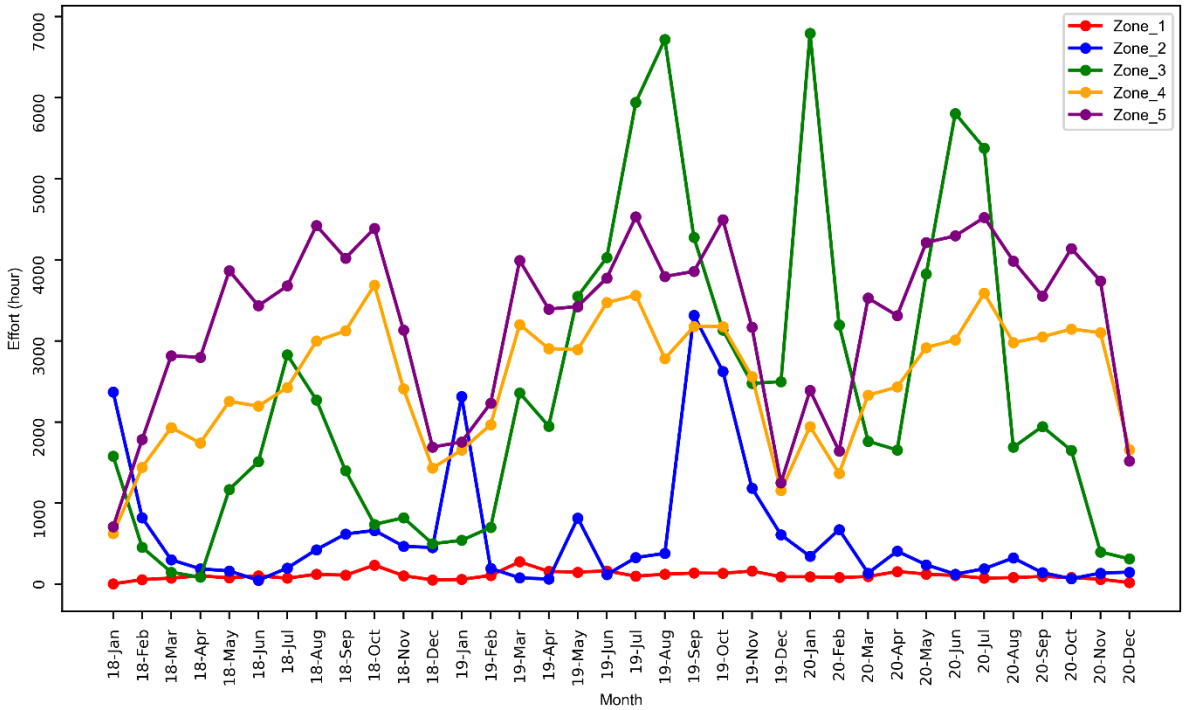


Fig. 2. The fishing effort of purse seine vessels targeting short mackerel in the GOT during 2018-2020. The map depicts the hourly total VMS position within 0.1° longitude × 0.1° latitude. The red line indicates the seasonal closure area.

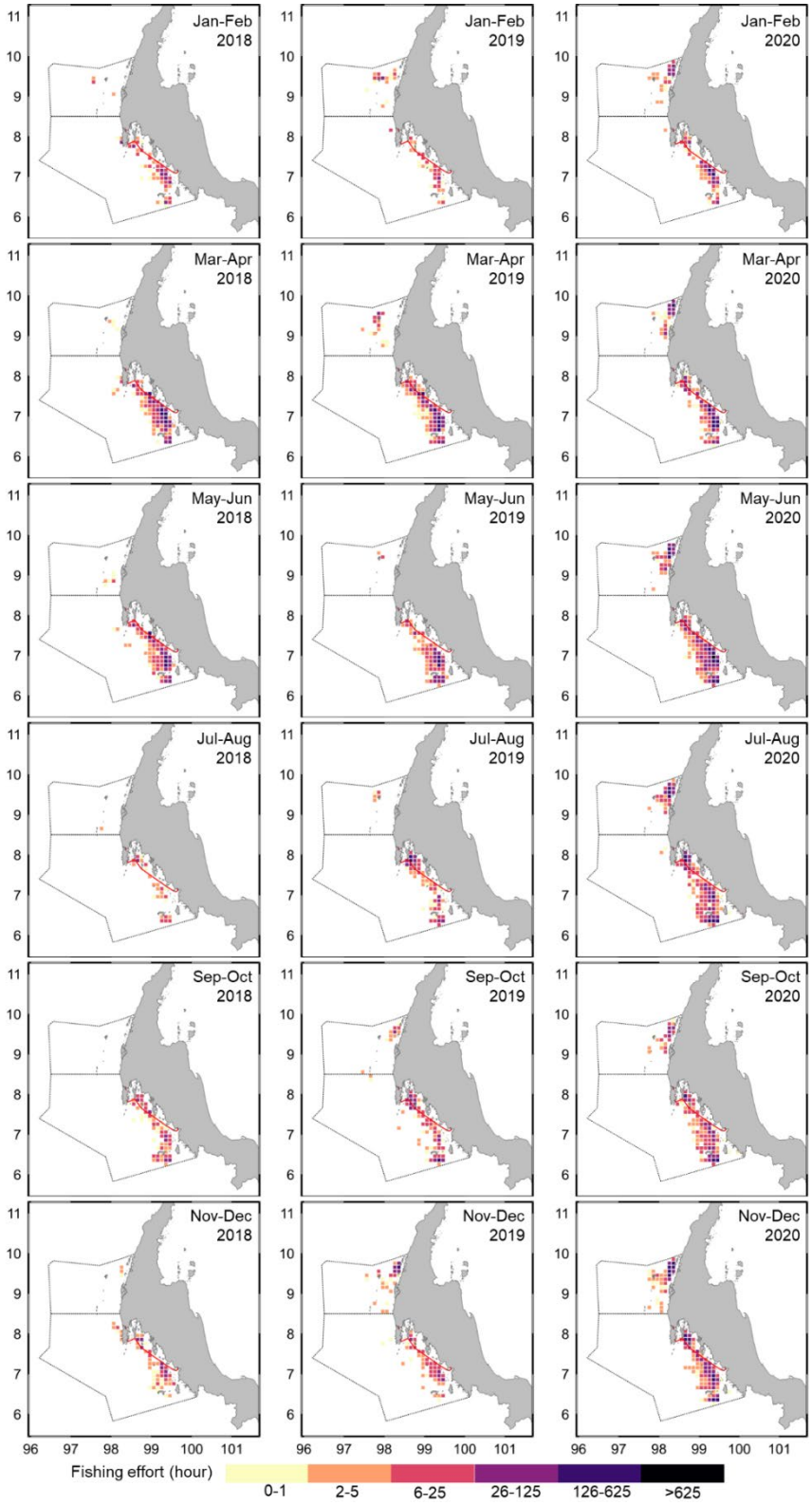


299

300 **Fig. 3.** The monthly fishing effort targeting short mackerel operated in the GOT is divided into five
301 management statistical zones (see Fig. 1).

302

303 Fishing in the GOT was considered monthly by the management zone, as depicted in Fig. 3.
304 Over 3 years, the fishing effort displayed a similar and consistent pattern in zones 4 and 5, increasing
305 during the seasonal closure from March to October and then decreasing to the end of the year until the
306 beginning of the following year. In Zone 3, the fleet effort tended to concentrate from June to July, a
307 similar pattern in all 3 years; however, the effort in Zone 3 was greater in 2019 and 2020 than in 2018.
308 In zone 2, fishing effort was highest in 2019, but with no clear pattern in that zone across the 3 years.



309

310 **Fig. 4.** The fishing effort of purse seine vessels targeting short mackerel in the ADS during 2018-2020.

311 The map depicts the hourly total VMS position within 0.1° longitude × 0.1° latitude. The black dot line

312 indicates the seasonal closure area.

313

Fishing in the ADS is illustrated in Fig. 4. The fishing operations recorded from VMS locations were 6,919 h, 8,626 h, and 20,510 h in 2018, 2019, and 2020, respectively. Three primary fishing areas were identified, with management zone 6 falling within the upper ADS and management zone 7 extending across the middle and lower ADS. The average distances between the fishing fleet and the shoreline in zones 6 and 7 were 9.42 ± 4.33 km and 12.12 ± 5.95 km, respectively. The fishing fleet in Zone 7 was distributed consistently, particularly in 2019 and 2020, when there was less effort at the start of the year (Fig. 5). The fishing effort in Zone 6 increased in 2019 and throughout 2020 (Fig. 5).

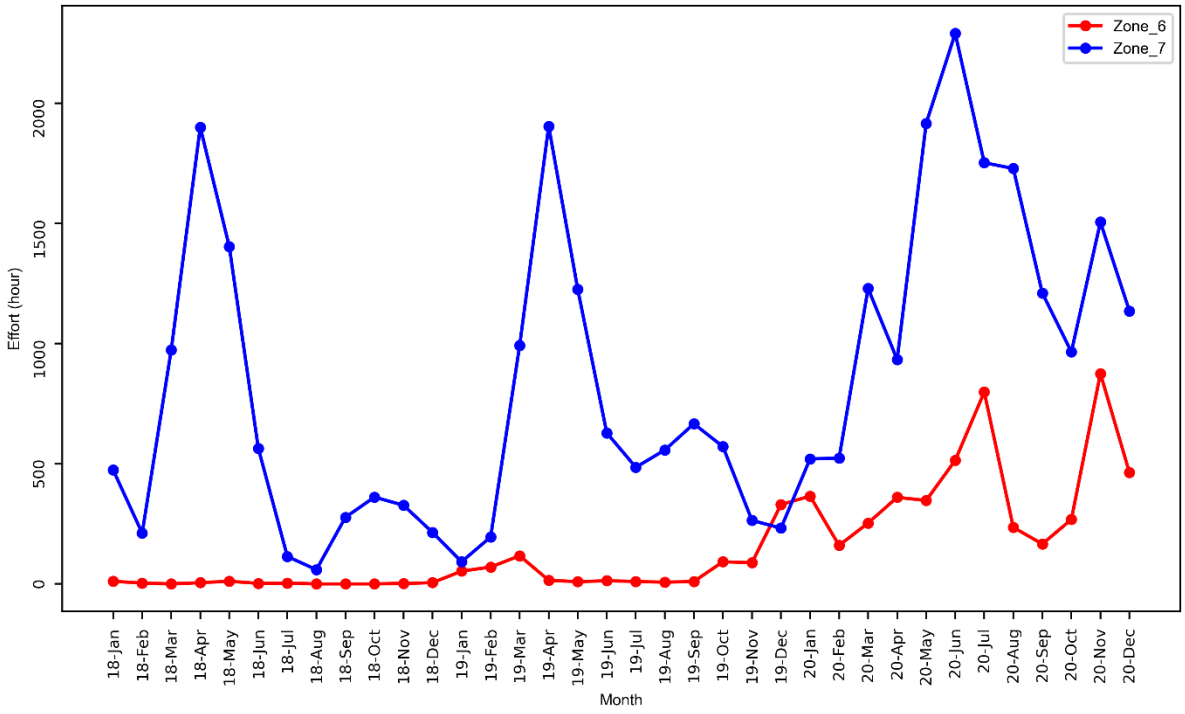


Fig. 5. The monthly fishing effort targeting short mackerel operated in the ADS is divided into two management statistical zones (see Fig. 1).

3.2. Spatiotemporal patterns in fish abundance

3.2.1. Model performance in predicting fish distribution

The RFR model performance for estimating fishing distribution in the GOT and the ADS, respectively, was 0.081 and 527.34 for RMSE and 0.05 and 217.35 for MAE.

3.2.2. Spatiotemporal distribution of fish abundance

The spatiotemporal distribution of fish abundance was examined by analyzing CPUE, measured as kilograms landed per day (Fig. 6). Over the 3 years, short mackerel in the GOT was dispersed across the management zones, with no significant spatiotemporal distributional trends

observed overall. However, the CPUE was notably highest in 2019, particularly in zones 2 and 3. Also, in September 2019, zone 2 had the highest CPUE among all the recorded data (Fig. 7).

The distribution of CPUE in the ADS is shown in Fig. 8. The CPUE in zone 6 was highest in 2019 and 2020. In contrast, CPUE in zone 7 did not exhibit any discernible trend over the 3 years (Fig. 9).

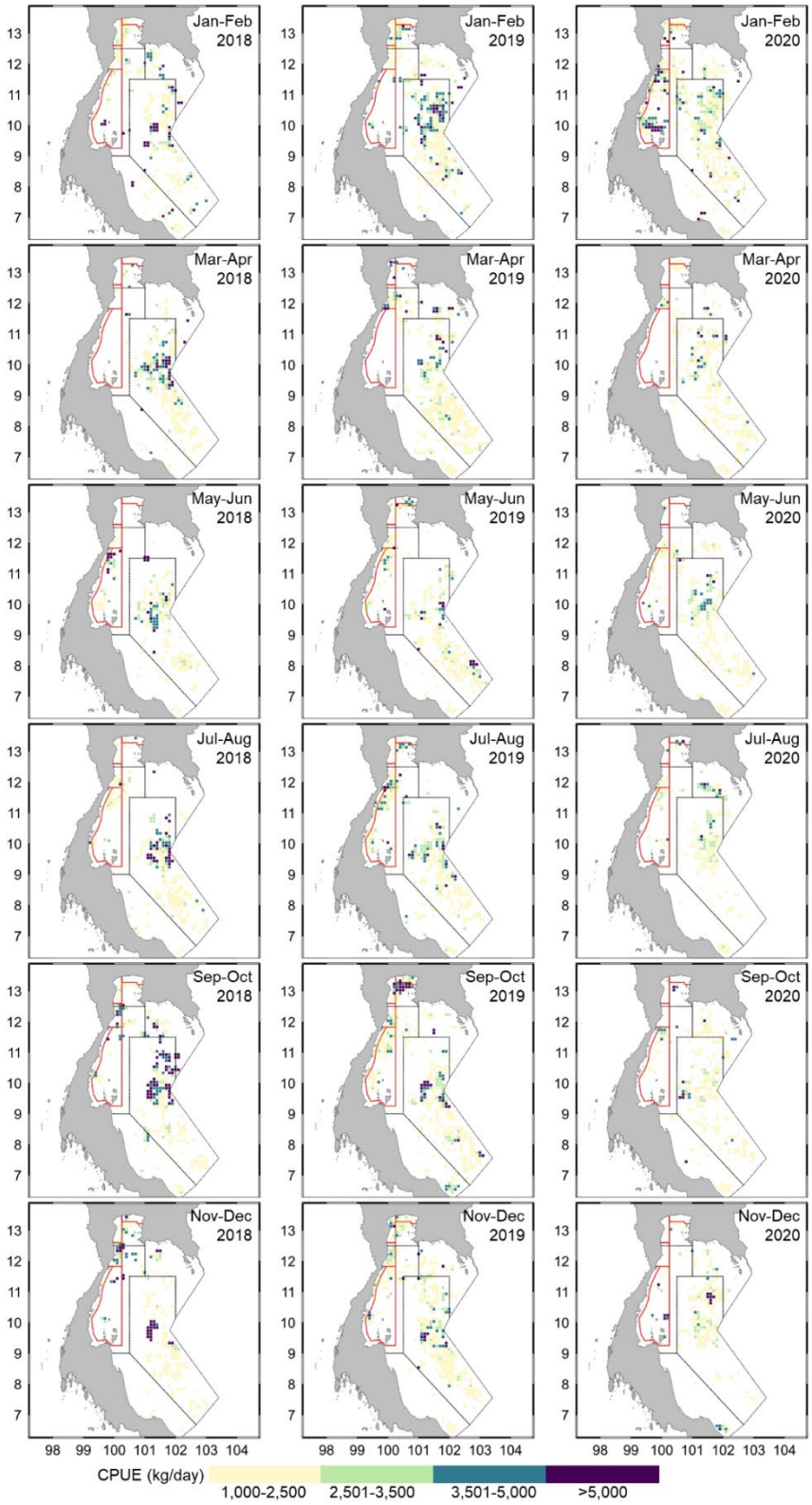
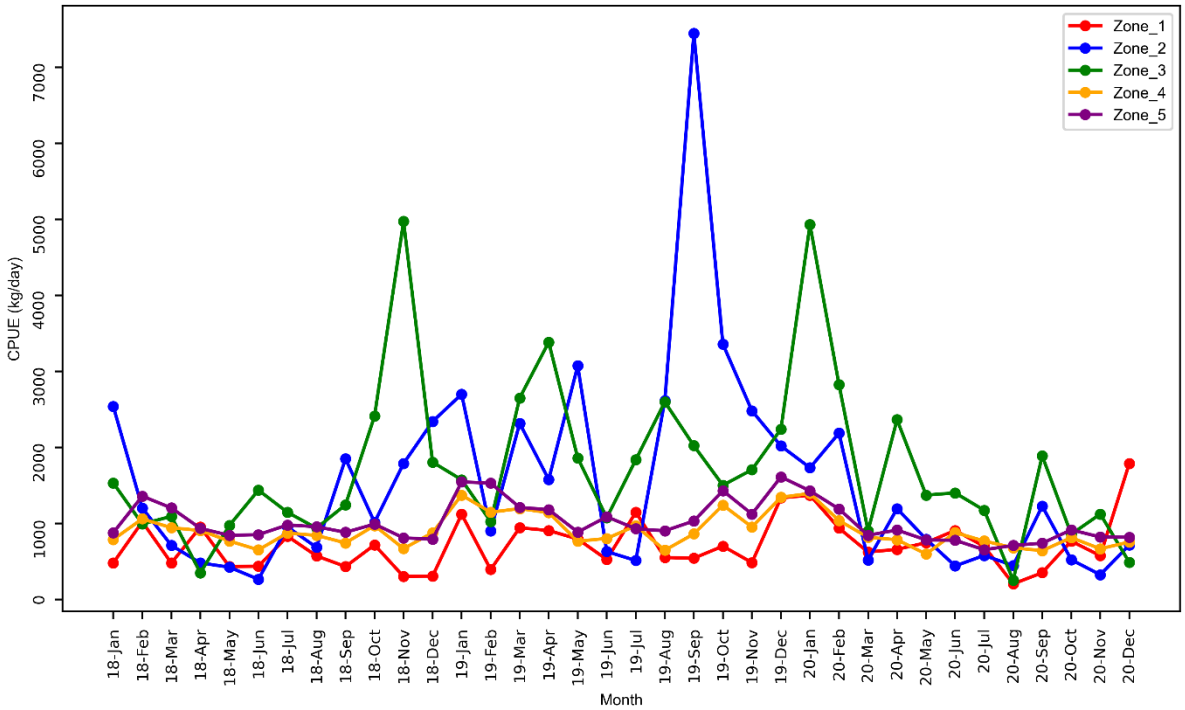


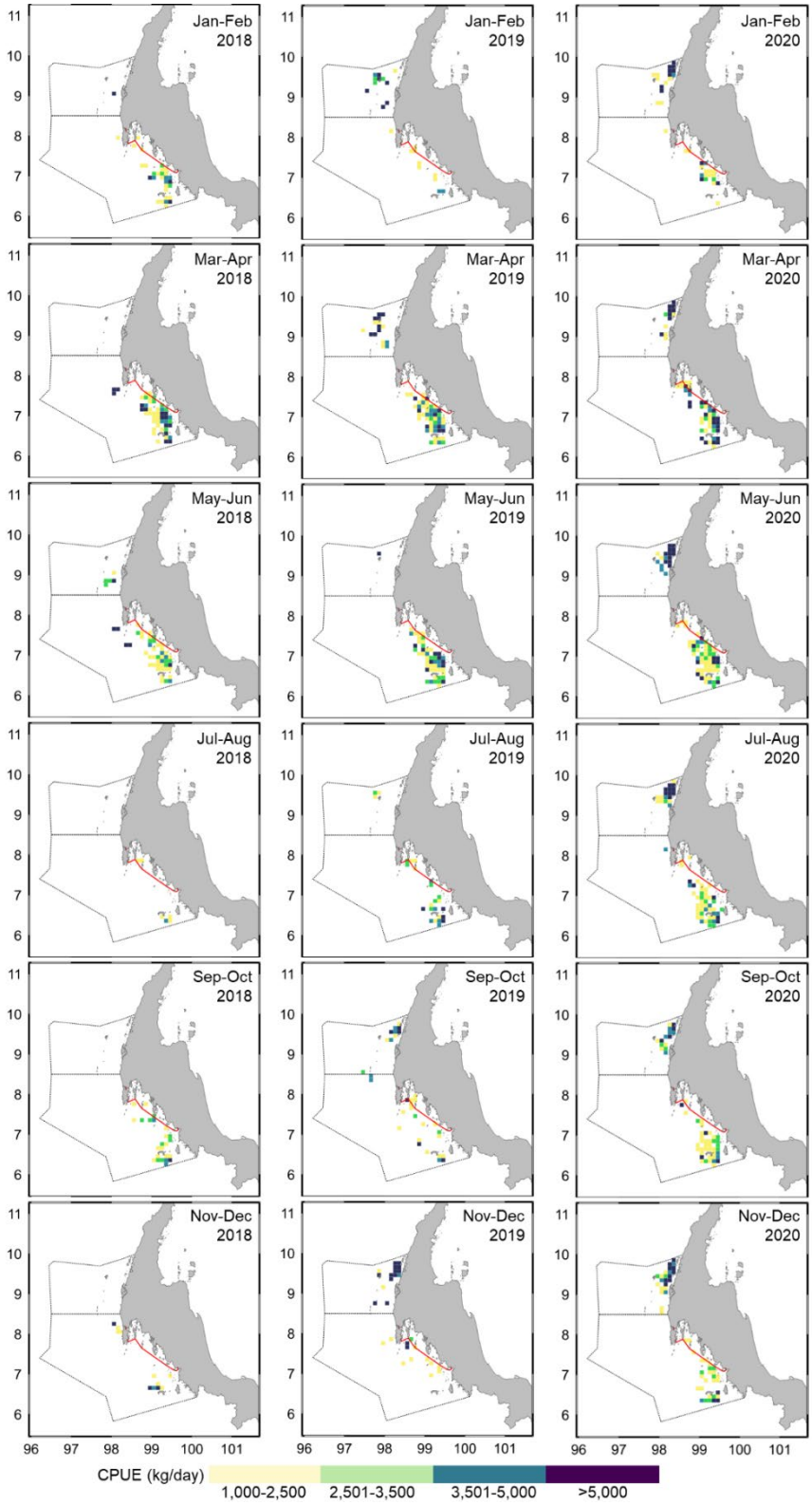
Fig. 6. CPUE distribution of short mackerel every two months occurred in the GOT between 2018 and 2020 within 0.1° longitude and 0.1° latitude. The red lines mark the area of the seasonal closure.



341

342 **Fig. 7.** The monthly CPUE distribution of short mackerel in the GOT is divided into five management

343 statistical zones (see Fig. 1).



344

345 **Fig. 8.** In the ADS during 2018-2020, the bimonthly CPUE of short mackerel was distributed within 0.1°

346 longitude and 0.1° latitude. The black dots denote the seasonal closure area.

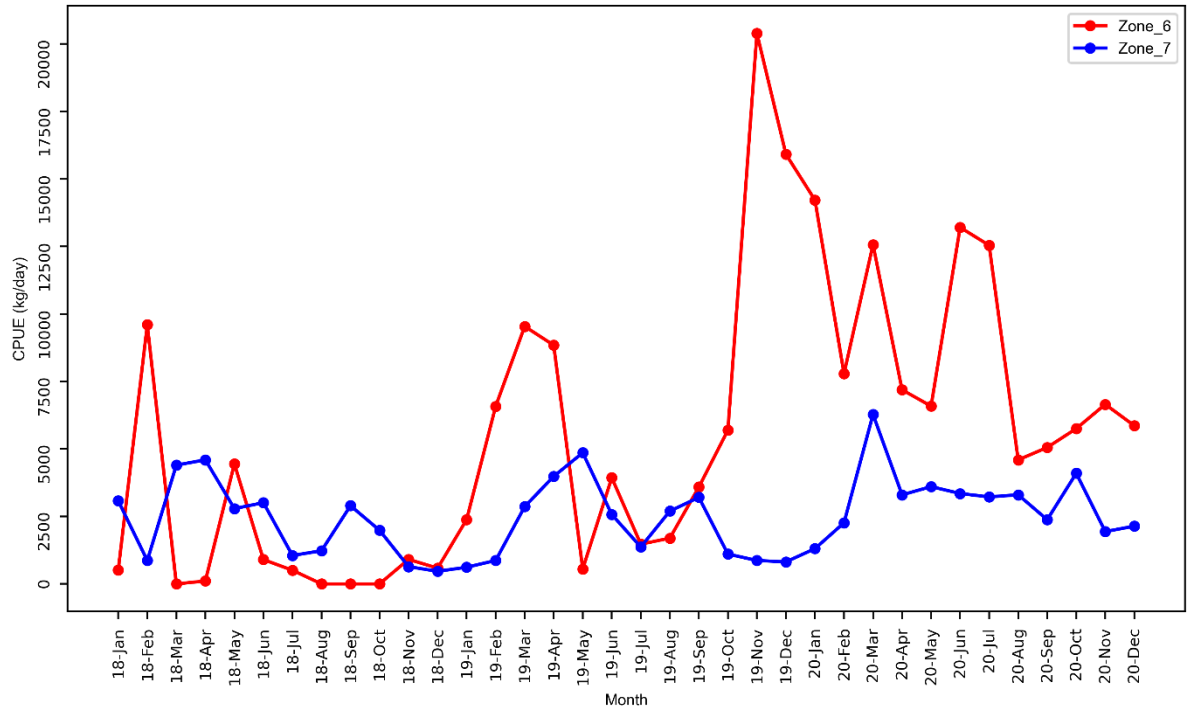


Fig. 9. The monthly CPUE distribution of short mackerel in the ADS is divided into two management statistical zones.

3.3. Fishing effort in relation to seasonal closures

Comprehensive monitoring of fishing activities throughout the fishing season showed that most purse seiners ceased fishing for short mackerel within the restricted area. However, a notable concentration of fishing activities in the GOT was detected along boundaries of the restricted area, specifically near management zone 3, during the initial seasonal closure (C1) in February and March, in both 2019 and 2020 (see Fig. 2). Furthermore, during the second closure (C2) in May and June, the vessels traveled nearer to the shoreline adjacent to the restricted area, revealing a discernible distribution pattern, as depicted in Fig. 2. Likewise, there was a substantial aggregation of fishing vessels near the borders of the restricted area during seasonal closures C3 and C4 in September 2019 (Fig. 2). Conversely, fishing activities in the lower GOT, when no seasonal closure was in effect, appeared to be more active during the closures in the upper and middle areas from February to September (Fig. 2). In the ADS, the fishing vessels relocated farther south during the single closure in April to June in zone 7, and thereafter returned to area, as detailed in Fig. 4.

4. Discussion

4.1. The effects of seasonal closures on fishing effort and fish abundance

Seasonal spatial closures may influence fleet dynamics. Fishing operations often demonstrate a remarkable ability to adapt to new circumstances, such as area closures, to maximize their limited fishing opportunities [33]. For instance, in this study, the fishing intensity in zone 3 began to increase in April and peaked in June, indicating consistent fleet movement in this zone during the 3 years (Fig. 3).

From a spatial perspective, in May, immediately after the end of C1, the fleet relocated closer to the coastline near the C2 boundary (Fig. 2). Even though the fishing effort at the time was considerable, the CPUE was not markedly high. Additionally, during C1 in February and March 2019 and 2020, the fishing operations were concentrated outside the restricted area and along the boundaries of Zone 3. This scenario represents a phenomenon known as vessels 'fishing inline,' which refers to fishing in the immediate area outside a closure. This tactic takes advantage of 'spillover' as fish stocks migrate from protected areas to nearby unprotected waters [34]. Even so, marine protected areas are sometimes established so that fisheries can benefit from such spillover [35]. Issues to consider in this context include possibly compensating certain harvesters or concentrating efforts on fewer fishing sites, particularly close to the reserve boundary [34,36].

Elevated fishing activity along specified borders during spatial closures highlights a need to consider the spatial distribution of fishing operations when implementing area closure measures. Abbott and Haynie [33] and Wilen et al. [37] suggest that failure to adequately consider commercial fishers' behaviour when designing management policies may result in implementation errors and can severely undermine the success of fisheries management measures. Given that fishers' behaviours contribute to fisheries exploitation, fisheries management needs to go beyond ecological and oceanographic factors and consider the behavioural dynamics of fishers as well [37].

Implementation of a time–area closure can induce competitive fishing behaviour, sometimes called 'derby fishing,' whereby fishers aim for the greatest catches within the shortest timeframe. This behaviour can also lead to fishing beyond sustainable levels [38].

This study observed the highest fishing effort and overall greatest catches in 2019. Alongside the 'fishing-in-line' behaviour identified during C1 and C2, we also observed a heavy concentration of the fishing fleet in the upper GOT during the C4 closure, particularly in September of 2019, near the outer boundaries of C4 (Fig. 2 and Fig. 3). Moreover, the peak CPUE in the upper GOT (Zone 2) was

recorded in September 2019, corroborating previous research indicating that Zone 2, despite being the smallest management unit in the GOT, serves as a major fishing ground [39]. This heightened abundance may prompt a substantial influx of fishing fleets to Zone 2 during this timeframe. Furthermore, there is discernible heightened fishing activity in the area, reflecting a pronounced concentration of fishing effort within comparatively restricted fishing areas. Consequently, this could lead to a decrease in the observed fish abundance during the same period and location in 2020 (see Fig. 3). A plausible explanation could be a depletion of the fish stock in the upper GOT owing to increased fishing pressure in September and October of 2019. Intensive fishing within a confined region could lead to the overexploitation of fish stocks, potentially impacting the population size in the subsequent year [40].

Seasonal closures are not used in management zones 4 and 5 in the lower GOT, where a consistent pattern of fishing effort was observed over the 3 years. However, once closures were implemented in the middle and upper GOT, an increase in fishing effort was observed in the lower GOT. This fishing effort dynamics suggests that the fleet travels farther south to access alternative fishing grounds.

Thai purse seiners target not only short mackerel as their primary catch but also other pelagic fishes. This study initially estimated the fishing locations based on trips targeting short mackerel; however, short mackerel may have been caught along with other species during those fishing trips, and, as a result, not every anticipated fishing location yielded catches of short mackerel. Furthermore, captures of short mackerel are typically recorded as *Rastrelliger* spp., in combination with catches of Indian mackerel *R. kanagurta* [17]. Although short mackerel may occasionally be ensnared and commingled with other species exhibiting analogous behavioural traits, our methodology successfully extracted the actual weight of the mackerel, sourced exclusively from landing data (refer to section 3.2.2 for elaboration), and reallocated it to the corresponding fishing positions obtained from VMS data. Consequently, this approach facilitates the discernment of the isolated distribution of mackerel abundance, notwithstanding any intermingling.

The ADS is subject to an annual area closure in part of zone 7 (near the coast) from 1 April to 30 June. Over the 3 years of the study, fishing activity in zone 7 exhibited a distinct pattern, with an increase from March to April, followed by a decrease in the middle of the ADS during the closure. Whereas no fishing occurred within the closure area, the higher concentration of fishing activity was

attributed to the fleet's southward movement in that zone. Subsequently, when the closure was lifted, the fishing fleet shifted toward the middle of the ADS.

Zone 6 in the ADS has an abundance of short mackerel [41]; this study revealed that fishing activity in that zone, initially low in 2018, rose in late 2019 and steadily increased in 2020. The movement of the fleet in the ADS during the closure differed notably from that in the GOT, where a distinct pattern was observed over 3 years; in the ADS, fishing was rarely concentrated near the boundaries of the closure area. Moreover, it was observed that the fishing efforts in the ADS were relocated to other areas during the closure, similar to the GOT observed that the movement of fishing efforts to the lower GOT during closures in the middle and upper GOT.

4.2. Uncertainty in fish abundance

The usefulness of time–area closures can be compromised when there is uncertainty about the dispersion of fish [11], as when the design of a time–area closure does not align with fish movements driven by migrating species or fails to use up-to-date information on fish abundance. In such cases, the closure should be revised [42]. Previous research has indicated that the primary spawning grounds of short mackerel are situated in the middle of the GOT (zone 3) and various areas within the inner GOT (zone 2) [24,39]. The peak of the spawning season in the middle GOT is reportedly between February and June [24,43], which justified the implementation of seasonal closures in the area. However, the present study found that CPUE in the short mackerel fishery, particularly in the GOT, did not exhibit a consistent pattern over the 3 years of observation (Fig. 6 and Fig. 7). The CPUE pattern is purely due to different distribution of the fish. The fleet size was similar throughout the study period because the registration of new fishing vessels and new fishing license issuance have not been allowed since 2019 to control the fishing effort. The purse seine net is designed to catch mixed pelagic species; therefore, the target species for purse seine is the same. This suggests that the species migrations and population dynamics in the region are characterized by instability and regular fluctuations.

Previous studies revealed the presence of multiple spawning grounds, significant genetic diversity, and at least four distinct populations of short mackerel in the GOT [18,44]. Although the short mackerel is a migratory species, with adults moving into more open and deeper water [17,18], there are indications that certain stocks move less or do not mix. For instance, stocks in the eastern (zone 1) and western (zone 3) GOT showed limited movement or mixing [24].

Moreover, genetic isolation suggests that short mackerel in zone 3 contribute the least to fishing grounds in the inner and eastern GOT. The migratory patterns and behaviours of short mackerel populations can influence population gene flow, as they may migrate in multiple directions in response to environmental and biological conditions [23]. Consequently, establishing a time and area closure to protect this migratory species becomes significantly challenging. Considering the unpredictability of the spatial and temporal distributions of short mackerel, it may be necessary to reconsider the seasonal closures and revise the structure of the protected area or implement a dynamic closure approach.

Dynamic closures are a relatively new fisheries innovation that needs enormous amounts of data to be analyzed rapidly to drive management decisions under either a co-management or self-governance approach [45, 46]. Various dynamic closures have been established in several countries that allow for the immediate closure of fisheries for short periods in specific zones, such as those with high abundance, locations in which an excessive amount of the catch consists of juvenile fish or sensitive species [10, 42]. Technology and infrastructure that support data collection, monitoring, and communication amongst stakeholders are essential to the design of the hotspot and define the threshold of catch rate for real-time spatial management. Dynamic closure management can encourage improved group decision-making if real-time information can predict fish stock dynamics [46]. Several dynamic closure management systems rely on observers on board, at sea inspection, or monitoring and enforcement systems such as VMS and daily landing to respond rapidly to changing hotspots. The effectiveness of the closure location approach depends on the dependability and analysis of VMS data as well as the correctness of logbook records [47]. According to the development of VMS, logbook data, and entirely documented fishing, this approach is now feasible with a significantly higher degree of spatial analysis and management through the consideration of a dynamic closure system instead of conventional fisheries management [46].

Surveillance data could potentially be used to support the implementation of both the current seasonal closure and the future dynamic closure. Policymakers can use seasonal closure to stay updated on ongoing policies. Presently, the seasonal closure measurement incorporates the assessment of the developmental stage of broodstock and the relative abundance of economically valuable fish larvae. The first three components of the current seasonal closure evaluation were conducted by the Marine Fisheries Research and Development Division, DOF. Data has been collected from commercial fishing vessels, fishing survey vessels, and biological information to confirm the

application of the recommended procedures. Suppose DOF uses the distribution data from all commercial fishing fleets and all landing trips used in this research, which covers all seasons.

Enhancing the clarity of the spatial and temporal distribution of fish would be beneficial. It is possible to verify inaccurate outcomes concerning the assessment of the mortality reduction rate. In order to facilitate the establishment of objectives aimed at mitigating mortality rates, managers must be supplied with the necessary tools and knowledge.

Furthermore, the utilization of classified surveillance data regarding fishing locations contributes to the enforcement of laws by effectively monitoring fishing operations in both spatial and temporal dimensions. It can be undertaken to ensure that the integrity of the area's closures remains intact and is not compromised by incidents of illegal fishing.

Although the current seasonal closures in the GOT are implemented primarily to protect the spawning grounds of short mackerel and address concerns of overexploitation, specifically in zone 3 and the inner GOT, the present study did not investigate spatiotemporal aspects of the spawning grounds or migration patterns of the different life stages. Nonetheless, it is crucial to regularly monitor the short mackerel resource at the commercial fishing grounds and track the fishing activities to reveal changes in the fishery for the sake of the long-term sustainability of this fishery in both the GOT and ADS [23].

5. Conclusions

This study presents an initial investigation undertaken in Thai waters that utilized vessel surveillance data for near real-time monitoring and analysis of changes in the fishing fleet dynamics and the abundance of short mackerel in a spatial and temporal context. The availability of VMS data offers significant advantages in terms of high spatiotemporal resolution and extensive coverage across the fishing season. This is crucial for determining optimal time–area closures and assessing the impacts of seasonal closures, taking into account the unpredictability of stock distribution and fleet behaviours, in conjunction with information on spawning grounds. Commercial fishing activity has a large share in the exploitation of marine resources. We emphasize the need for further research to evaluate the effectiveness of static seasonal closures and to consider alternative time–area closure measures that address overexploitation and promote sustainability.

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