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Combining catch-based indicators suggests overexploitation and poor status of Indonesia's deep demersal fish stocks

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A R T I C L E I N F O

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A B S T R A C T

The Indonesian deep-slope demersal fisheries are economically valuable and contribute to the wellbeing of millions of people. However, the sustainability of these fisheries is uncertain because they lack data and assessment. As a precursor to management, we developed and applied a framework for using standardized catch per unit effort (CPUE) and spawning potential ratio (SPR) as indicators to assess eight primary species-fishing gear complexes: the Malabar blood snapper *Lutjanus malabaricus* (droplines and longlines), goldbanded jobfish *Pristipomoides multidens* (droplines and longlines), sharptooth jobfish *P. typus* (droplines and longlines), crimson snapper *L. erythropterus* (droplines), and rusty jobfish *Aphareus rutilans* (droplines). We standardized CPUE by identifying relevant fishing trips using a species-association approach and removing any changes in the index not attributable to abundance by using a delta-generalized linear model. SPR values were estimated on a per-recruit basis from life-history parameters using length data. Results indicated that in 2020, all stocks were unhealthy (SPR values < 25%) with only a few exceptions (e.g., *P. multidens* and *L. erythropterus*). Most fishing grounds with low SPR values had stable or decreasing CPUE trends, suggesting that current fishing rates are suboptimal or unsustainable. However, *L. erythropterus* had an increasing CPUE trend but moderate to low SPR, indicating that fishing pressure has decreased so SPR may be an underestimate, leading to an optimistic but uncertain conclusion about stock health and the sustainability of current fishing rates. Such discrepancies between CPUE and SPR may be challenging for the implementation of management measures, but we have outlined and applied a framework for interpretation. The most recent yield values set by the Indonesian Ministry of Marine Affairs and Fisheries for these stocks, however, are 1.4–2.4 times higher than our calculations. This discrepancy may be attributed to several factors, such as inclusion of species that are atypical for deep demersal fish stocks in the Ministry's estimates, differences in methods or the types of data used, or annual variability.

1. Introduction

The Indonesian deep-slope demersal fisheries have helped position Indonesia to be the world's second largest exporter of snapper species (Cawthorn and Mariani, 2017). The top two species, Malabar blood snapper (*Lutjanus malabaricus*) and the goldbanded jobfish (*Pristipomoides multidens*), have a combined domestic and international market value of $382 million USD and $176 million USD, respectively (Mous et al., 2020). The fisheries are multi-species and multi-gear, predominantly targeting snappers (Lutjanidae) and groupers (Epinephelidae) between 50- and 500-meters (Wibisono et al., 2022). Depending on the bathymetry and habitat type, fishers use different

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gears; droplines (vertical lines or buoy gears) and longlines (bottom or set longlines) are by far the most important gear types, but fish traps and bottom gillnets are also used in some instances (He et al., 2021). Vessel sizes vary from small artisanal boats to very large industrial fleets, or < 1–150 gross tonnes (GT). Despite differences in habitat types throughout Indonesian waters, the fisheries operate throughout the Indonesian Fishery Management Areas (FMAs), i.e., the boundaries within the Indonesian archipelago that delineate fisheries data monitoring and management areas. Particularly important FMAs for the deep-slope demersal fisheries include FMA 711 (South China Sea), FMA 712 (Java Sea), FMA 713 (Makassar Strait), and FMA 718 (Arafura Sea; Mous et al., 2020).

Indonesia's primary management measure that is currently used is a licensing system, which aims to regulate fishing capacity towards a Total Allowable Catch (TAC). The TAC is set at 80% of the maximum sustainable yield (MSY). MSY is estimated for nine species groups (small pelagics, large pelagics, demersal fish, reef fish, penaeid shrimps, lobsters, crabs, blue swimming crabs, squids) in each of Indonesia's 11 FMAs by the National Committee on Fish Stock Assessment using catch statistics, fisheries-independent data (trawling and acoustic data), and applying a surplus production model. The most recent MSY estimates are from 2017 (Ministerial Decree 50, 2017). The Indonesian Ministry of Marine Affairs and Fisheries (MMAF) estimates fishing capacity using productivity estimates, which are expressed as annual catch (t) per gross tonne (GT). The productivity estimates are documented in a ministerial decree (Ministerial Decree 87, 2021). Each fishing gear is characterized by a specific catch composition and the approximate volume of catches are estimated based on vessel size. From the calculated MSY, the MMAF estimates the total GT allocated in each FMA and then the licenses are distributed based on this total allocation, while making sure that the total amount does not exceed the TAC.

Like other deep-water fisheries in the tropical and subtropical Pacific Ocean, quantitative stock assessments of Indonesian stocks have been limited due to the scarcity of biological and fisheries data. National data collection has been based on logbooks, which are frequently inaccurate and utilize general species complexes such as 'snapper' instead of more detailed species names (Proctor et al., 2003; DeMartini, 2019). Many of the deep-water species have slow growth rates, late ages at maturity, and extended longevities, making them particularly vulnerable to over-exploitation (Newman and Dunk, 2003). In addition to slow growth rates, many of the demersal species aggregate around distinct habitat formations such as seamounts and ledges, which may lead to boom-and-bust population dynamics that are challenging for assessment (Francis, 1992; Williams et al., 2013). The use of indicators to assess fish stocks may be a viable solution that balances data needs and feasibility in a context like the Indonesian deep-slope demersal fisheries; using multiple indicators in data-poor scenarios to assess fish stocks is a rapidly advancing and promising field in fisheries science (Harford et al., 2021).

Catch per unit effort (CPUE) can be relative to abundance and is expected to decline with abundance and in response to increasing fishing effort (Table 1) (Hilborn and Walters, 1992; Ault et al., 2014). Without an unfished baseline value for comparison, CPUE alone can only indicate potential relative changes in abundance (but without knowing if the current abundance is healthy or depleted). Unfished baseline CPUE values can occasionally be inferred from historical data, catches from marine protected areas, or a comparable pristine habitat, but these circumstances are rare (Campbell et al., 2007; Wilson et al., 2010). In general, and especially when CPUE is measured from fishers whose behavior can change in response to a wide range of socioeconomic and management-related factors, it needs to be standardized to remove external effects that impact catch rate and account for inconsistencies in fishing patterns and environmental factors (Chiarini et al., 2022; Maunder and Punt, 2004). A goal of standardizing the CPUE is to reduce the noise and variance in catch data and amplify the signal in abundance. Therefore, standardized CPUE is a useful indicator for evaluating the impacts of fishing effort on abundance and identifying variables that affect catch rates (Maunder et al., 2006).

Spawning potential ratio (SPR) is the relationship between reproductive potential (i.e., the expected egg output of an average individual fish throughout its expected lifetime when the population is fished), divided by the individual's expected egg output if the population were not fished at all (Quinn and Deriso, 1999; Meester et al., 2001). Thus, SPR takes on values between 0% (resource fully depleted) and 100% (resource unexploited) (Brooks et al., 2010). For SPR, target conservation reference points are commonly set at 40%, and 20–30% is set as a limit reference point below which recruitment may be severely impaired (Table 1) (Mace and Sissenwine, 1993; Mace, 1994). However, reference points are highly dependent on life histories and models can be used to predict stock-specific reference points from life-history parameters (Zhou et al., 2020). In a harvest control strategy, fisheries that have values below the limit reference point will trigger a series of management actions to reduce fishing effort and bring the SPR back to the target (Gabriel and Mace, 1999). A major strength of the SPR approach is that the current SPR is given relative to an unfished, pristine reference point, something that can provide insight on approximate MSY conditions and thus the health of the fish stock. On the other hand, a major weakness of SPR is that it assumes equilibrium conditions, a potentially invalid assumption if there have been recent inconsistencies, for example in recruitment or fishing pressure and data collection methods. This is where CPUE can complement SPR by supporting or challenging the interpretations of SPR that assume consistency.

CPUE and SPR are utilized and interpreted differently. CPUE is an indicator of relative fishing abundance, and therefore stock trend, that incorporates catch relative to effort. SPR is an indicator of relative fish biomass in the stock. When considered together, they can be used to assess fish stocks and provide management advice on controlling fishing effort (Table 2). However, contradictory results may arise such as a decreasing CPUE with a high SPR. In such a scenario, an evaluation framework is needed to interpret results and provide fisheries managers with guidance. In this study, we develop such a framework and use it to assess the status of species in the Indonesian deep-slope demersal fisheries. Specifically, we focus on eight species-fishing gear complexes that represent the most abundant fish species in the fisheries, i.e., *Lutjanus malabaricus*-dropline and longline, *Pristipomoides multidens*-dropline and longline, *P. typus*-dropline and longline, *L. erythropterus*-dropline and *Aphareus rutilans*-dropline. We aimed to: 1) calculate a time series of annual standardized CPUE values for each species-gear complex, 2) estimate the standardized CPUE index of prominent fishing grounds in each FMA, 3) compare the CPUE index with SPR values in each FMA, 4) compare CODRS productivity estimates with respective values provided by the MMAF, and 5) discuss potential management options and implications based on the comparison between the standardized CPUE, SPR, and MMAF productivity values.

Table 1
Standard interpretations of single indicator results for catch per unit effort (CPUE) and spawning potential ratio (SPR) values and trends.

Single indicator result	Standard interpretation
CPUE trend	
Increasing	The stock appears to be growing.
Stable	The stock appears to be stable.
Decreasing	The stock appears to be declining.
SPR (assuming equilibrium conditions)	
High ($\geq$ 40%)	The stock appears to be healthy.
Moderate (25–40%)	The stock may be overfished.
Low ($\leq$ 25%)	The stock is likely overfished.

Table 2
Interpretations of the combination of indicator results for catch per unit effort (CPUE) and spawning potential ratio (SPR) trends and values.

CPUE trend	SPR	Combined interpretation
Increasing or stable trend	High (≥ 40%)	Indications that the stock is healthy and current fishing rates may be sustainable.
Decreasing trend	High (≥ 40%)	Indication that fishing pressure has increased so SPR may be an overestimate, leading to less certainty about the health of the stock and the sustainability of current fishing rates.
Increasing trend	Moderate (25–40%)	Indication that fishing pressure has decreased so SPR may be an underestimate, leading to an optimistic but uncertain conclusion about stock health and the sustainability of current fishing rates.
Stable or decreasing trend	Moderate (25–40%)	Indications that the stock is unhealthy and current fishing rates may be suboptimal (stable) or unsustainable (decreasing).
Increasing trend	Low (≤ 25%)	Indication that fishing pressure has decreased so SPR may be an underestimate, but likely that the stock is in poor health but showing signs of recovery.
Stable or decreasing trend	Low (≤ 25%)	Indications that the stock is unhealthy and current fishing rates are suboptimal (stable) or unsustainable (decreasing).

2. Materials and methods

2.1. Data sources

Data for this study were collected through the Crew-Operated Data Recording System (CODRS), which has been implemented across the Indonesian Exclusive Economic Zone (EEZ) by The Nature Conservancy (TNC) and its affiliate Yayasan Konservasi Alam Nusantara (YKAN), in collaboration with the MMAF; it is the first documented multi-species data collection program of this scale in tropical fisheries (Wibisono et al., 2021 and 2022). The CODRS dataset consists of fishing information (i.e., fishing gear and vessel size), catch information (i.e., species and length), and location data. Participating fishers are equipped with a measuring board, camera, and a GPS tracking device that records vessel coordinates at every hour. In CODRS, fishers are required to take photographs of their entire catch on a measuring board during fishing. Data from CODRS represent fishing activities in all Fisheries Management Areas (FMAs) (Fig. 1). The FMAs represent units for fisheries monitoring and management in Indonesia (Menteri Kelautan dan Perikanan Republik Indonesia, 2014). As each FMA is characterized by different habitat characteristics and bathymetry, a variety of fishing gears are used in each area, thus leading to different catch compositions (Fig. 1). In this study, we used CODRS data from January 2016 to December 2021, amounting to 13,632 fishing trips. We focused on the two main fishing gears, (i.e., droplines and longlines), as well as five of the most abundant (in terms of number of individuals and biomass) species in the catch (i.e., Malabar blood snapper - *Lutjanus malabaricus* (n dropline= 310,486, n longline= 389,107), golbanded jobfish - *Pristipomoides multidens* (n dropline= 343,672, n longline= 216,802), sharptooth jobfish - *P. typus* (n dropline= 221,444, n longline= 47,404), crimson snapper - *L. erythropterus* (n dropline= 154,734), and Rusty jobfish - *Aphareus rutilans* (n dropline= 106,206).

2.2. Fishing ground coordinates and number of fishing days

To assign fishing locations to photographs of fish, we matched the date and time on each photograph to that of the GPS coordinates. Depending on the vessel size, photographs may be taken on the same day as the fishing day. Smaller vessels < 10 GT tend to wait until the end of the fishing trip to take the photographs due to space constraints. Note that this practice means the fishing locations may be wholly inaccurate for small vessels, but they do not typically travel far from their home port (i.e., cross FMA boundaries). The number of fishing days was defined as the sum of all days with matching photographs in a single fishing trip. If there were multiple coordinates in a day, we used the average of the latitude and longitude for that day. We then interpolated the depth using 15 arc-second bathymetry data from the General Bathymetric Chart of the Oceans (GEBCO, 2020). To exclude potentially erroneous fishing coordinates, we only utilized fishing location coordinates from depths of 0–500 m.

2.3. Calculating CPUE

We calculated the nominal CPUE (kg/fishing day) by dividing catch by effort per identified fishing trip. The standardized CPUE was the product of the probability of a positive catch and the unbiased estimated CPUE of the target species. The unbiased estimated CPUE is the CPUE estimate that accounts for transformation bias when doing inverse transformation from a lognormal distribution (Miller, 1984). We defined catch as the total weight (kg) of each species in a fishing trip and effort as the number of fishing days in a fishing trip (fishing days). Fish weight was converted from length using the length-weight conversion equation:

$$W = aL^b$$

where W was weight (g), L was length (cm), and a and b were the

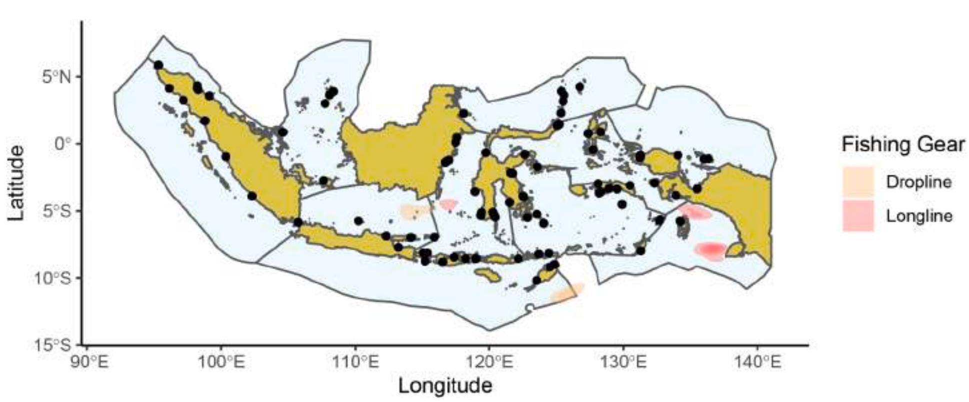

Fig. 1. Map of the Crew-Operated Data Recording System (CODRS) sites, i.e., fishing villages or ports where CODRS was deployed (black dots). Black lines denote Fishery Management Area (FMA) boundaries, and colored areas denote prominent fishing grounds per fishing gear.

length-weight conversion parameters (Supplementary Table S1). The length-weight parameter estimates were selected from available studies based on proximity to our study area, number of samples, and content availability. When there were no values found for a species, we used morphologically similar species to obtain the length-weight coefficients (see also Wibisono et al., 2022).

For each species-fishing gear complex, the CPUE standardization process included (i) the identification of relevant fishing trips, (ii) the fitting of a delta-GLM model to the data [both binomial (the probability of encountering a species) and lognormal (CPUE of fishing trips where the target species is encountered) models], (iii) the creation of a reference grid to predict or estimate the estimated marginal means (EMM), and (iv) the calculation of the standardized CPUE index (along with its 95% confidence intervals) (Fig. 2). Different reference grids were used to estimate the annual standardized CPUE index per species-fishing gear complex and the standardized CPUE index per fishing ground in 2020 (Fig. 2).

2.4. Identifying relevant fishing trips

Individual fishing trips can contain multiple species. Therefore, we calculated the standardized CPUE by analyzing fishing trips relevant to each of the target species (*L. malabaricus*, *P. multidens*, *P. typus*, *L. erythropterus*, and *A. rutilans*) (Maunder and Punt, 2004; Stephens and MacCall, 2004). In the absence of detailed habitat information on the target species, we used a species-association approach that identified relevant fishing trips through logistic regression based on the catch composition from each fishing gear (Stephens and MacCall, 2004). We used the regression coefficients from each species in the catch to compute the estimated probability that the target species would have been encountered in the fishing trip (Stephens and MacCall, 2004). Each fishing trip was assigned a trip score (S_j), which was a function of the species caught in the fishing trip:

$$S_j = exp\sum_{i=0}^{k} x_{ij}\beta_i$$

where:

x is the presence or absence of non-target species i in trip j, β_1, β_2, …, β_k are the coefficients from the logistic regression for species k that is also caught in the trip and β_0 is the intercept.

The trip score was converted into the predicted probability (π_j) of observing the target species (Y=1 for trip j):

$$\pi_j = Pr\{Y_j = 1\} = \frac{S_j}{1 + S_j}$$

The trips that were used in the subsequent CPUE standardization process had an estimated π_j that was above a critical value. The critical value, unique to each species-fishing gear complex, was a value that minimized the false positives and false negatives of the predicted fishing trips by using an F1 score.

2.5. Model selection

We utilized the delta-GLM model in the standardization process to account for zero catches in a fishing trip (Vignaux, 1994; Stefansson, 1995). The general form of the delta model is:

$$\Pr(Y = y) = \begin{cases} w, & y = 0 \\ (1 - w)f(y) & otherwise \end{cases}$$

where y is total weight of the target species (kg), w is the probability of zero observation of the target species, which was modeled using the binomial distribution with a logit link function, and $f(y)$ is the mean CPUE of positive fishing trips, which was modeled using the lognormal distribution, meaning that zero-values were excluded from the analysis.

We included year as a predictor variable in the binomial (the probability of encountering a species) and lognormal (CPUE of fishing trips where the target species is encountered) models for all species (Supplementary Table S2) irrespective of its significance because it was a variable of interest that allowed us to detect temporal (annual) and spatial differences (Maunder and Punt, 2004). We chose the explanatory variables from available data, such as FMA, depth (m), vessel size (GT), and month. We used a forward step-wise approach to choose the variables. To ensure the validity of the step-wise regression approach, we compared the AIC between the model that was selected through the forward step-wise approach and the model using just the variable of interest (year). Finally, we included variables that minimized the AIC. We also tested the variables of each model for collinearity. To assess the model fit, we calculated the D^2 (proportion of deviance explained) for each model, as well as the adjusted D^2 values, which consider the number of observations and the number of predictors, thus allowing direct comparison among different models (Guisan and Zimmermann, 2000).

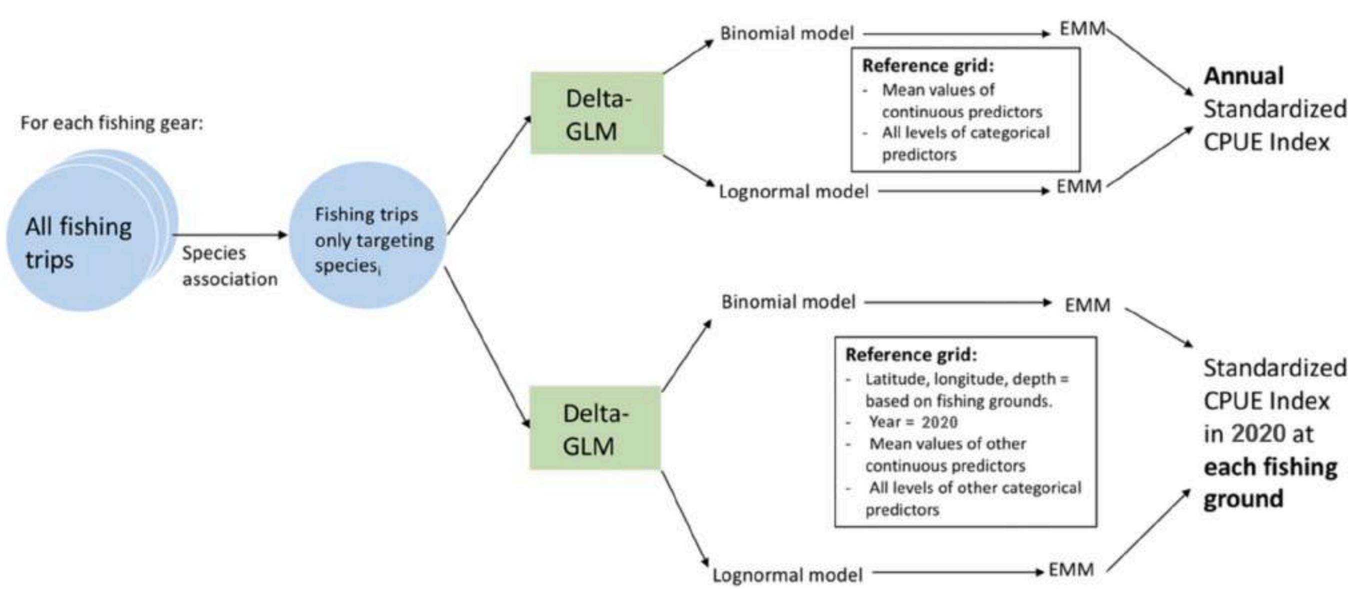

Fig. 2. Overview of the catch per unit effort (CPUE) standardization procedure to estimate (a) the annual standardized CPUE index and (b) the standardized CPUE index in 2020 at each fishing ground. EMM = Estimated Marginal Means (or least square means).

2.6. Standardized CPUE

To calculate the probability of a positive catch and unbiased estimate of the CPUE, we calculated the estimated marginal means (EMM, or least squared means) of both the binomial (the probability of encountering a species) and lognormal (CPUE of fishing trips where the target species is encountered) components of the delta-GLM model over a reference grid of predictors using the 'emmeans' package in R. The EMM represented the weighted averages of predicted probability of a positive fishing trip and the weighted averages of predicted CPUEs based on the values in the reference grid. To estimate the annual standardized CPUE, the reference grid consisted of the mean values of each continuous predictor (depth, vessel size) and levels of categorical predictors (FMA, month, year) (Supplementary Table S2). To estimate the standardized CPUE per fishing ground we used a different reference grid: we set the latitude, longitude, and depth that represented prominent fishing grounds and we chose to present 2020 to represent a recent point of the data collection time series. All other continuous or categorial variables were included in the reference grid as means. The prominent fishing grounds for each species-fishing gear complex were identified by using the kernel density estimator on the estimated fishing ground coordinates and the 'MASS' package in R (Venables and Ripley, 2002). We identified the latitude, longitude, and depth of prominent fishing grounds by determining the local maxima of each kernel density.

To get an unbiased estimate of the CPUE per year from the lognormal model, we back-transformed the lognormal EMM and applied a bias corrector to account for transformation bias (Lo et al., 1992):

$$\widehat{d}_k = \exp(\gamma_0 + \gamma_{1k})\psi_{\widehat{d}_k}$$

where:

$\widehat{d}_k$ = unbiased estimate of the CPUE of the target species.

γ_0 = mean log(CPUE) for the reference year (2016).

γ_{1k} = main effects of year k.

$\psi_{\widehat{d}_k}$ = correction for bias.

The bias corrector and confidence intervals of the standardized CPUE were calculated through the delta method (Bradu and Mundlak, 1970; Seber, 1982) (Supplementary Document S1). To detect relative annual changes in CPUE trends, we normalized the standardized and nominal CPUE around their respective means and we fitted linear regression models while considering outliers based on Cook's distance and filtering out values greater than 3 times the mean (Cook and Weisberg, 1984).

2.7. Calculating SPR

The spawning stock biomass (SSB) per recruit estimates the expected reproductive potential (i.e., fecundity, egg output) of an average individual. The ratio of the SSB of a fished population over the SSB of a pristine population, that would have existed in the absence of fishing, is known as the spawning potential ratio (SPR) and is used as a measure of the impact of fishing on the reproductive output of a population expressed as the degree of departure from its virgin condition (Goodyear, 1993). The maximum value SPR equals 1 or 100% in an unexploited stock and declines towards zero as fishing mortality increases removing all mature female fish and leaving a stock with no spawning potential (Hordyk et al., 2015). SPR has its strengths and weaknesses as a measure of stock status. As such, SPR is rather used as a proxy metric to understand the status of a stock by providing target or limit reference points for fisheries managers when there are insufficient data (lack of biological studies and long-term datasets) to determine the stock-recruit relationship (Camp et al., 2021).

SPR (%) values used in this analysis were derived from Mous et al. (2020) that uses CODRS length data to calculate SPR (by species, year, and FMA) on a per-recruit basis from life-history parameters of natural mortality (M), fishing mortality (F), growth, asymptotic length (L_{inf}), and gear selectivity parameters as described in Dimarchopoulou et al. (2021) and Wibisono et al. (2022) where the reader is referred for further methodological details (see the Supplementary Material of Dimarchopoulou et al., 2021 for the R code of the age-based model used to calculate SPR). The equilibrium Beverton-Holt estimator was used to calculate the instantaneous total mortality (Z = M + F) from length data applying the Ehrhardt & Ault (1992) bias-correction. For this estimation, we used the catch length-frequency distribution taking into consideration the range from the length that is 5% higher than the modal length to the 99th percentile, as it is an accepted practice to omit the right hand side of the length-frequency distribution that is too close to L_{inf} (Sparre & Venema 1998). We calculated F as the difference between Z and M, assuming full selectivity for the size range between the modal length and the largest fish in the catch. We assumed an S-shaped (logistic) selectivity curve, with the length at 50% selectivity halfway between the first percentile and modal length of the catch LF distribution and with 99% selectivity achieved at modal length. The calculation of SPR also accounted for maturity, and assumed it to be knife-edged, where fish in age or length bins that were below the age/length at maturity were assigned 0 and fish above that value were assigned 1. Length at maturity (L_{mat}) was calculated from asymptotic length L_{inf} which for deep-water snappers (Lutjanidae) was $L_{mat} = 0.59 * L_{inf}$ (Dimarchopoulou et al., 2021).

The length-dependent M to be used in the SPR estimation was calculated with an empirical formula that relates M to length (from CODRS data) and growth (literature-derived K and L_{inf} calculated from the CODRS maximum length L_{max} based on the published relationship $L_{inf} = 0.9 * L_{max}$ of Nadon and Ault 2016) characteristics (Gislason et al., 2010). A multiplicative correction factor (CF = 0.67) was applied to the formula to correct for the unrealistically high estimates of M for the tropical deep-water snappers targeted here (it should be noted that the introduction of the correction factor did not put the modified formula outside its original confidence limits) (Mous et al., 2020):

$$M = \frac{CF * 1.733 * K * L_{\infty}^{1.44}}{L^{1.61}} \quad (1)$$

(Reworked from its original notation as a log-transformed model).

While the catch curve analysis assumes a constant Z over the size range that is used for its estimation, Gislason et al. (2010) demonstrate that natural mortality varies with size. To deal with this inconsistency, we applied the adjusted Gislason et al. (2010) empirical relationship to the length classes over which we estimated Z. Then we calculated the average M over these size classes and applied that average to the size range over which we estimated Z. Outside this size range, a varying M was assumed following the modified Gislason et al. (2010) relationship.

2.8. Combining standardized CPUE and SPR per fishing ground

The combination and comparison of standardized CPUE levels and SPR calculations by fishing ground was done on the prominent fishing grounds for the six fish species of interest. SPR calculations were done with the method analyzed above on an FMA and species level for the most recent year with fully available data, i.e., 2020. We categorized an FMA as being at high risk of overfishing that might result in lower recruitment when SPR $\leq$ 25%, medium risk when SPR $>$ 25% and $<$ 40%, and low risk when SPR $\geq$ 40% (Table 1) (Mace and Sissenwine, 1993; Mace, 1994; Mous et al., 2020; Dimarchopoulou et al., 2021). We categorized a fish stock as declining (and of concern) when standardized CPUE trends were statistically significant and decreasing over the entire time series. If the standardized CPUE trend was statistically insignificant or stable, we classified the stock as stable. When the standardized CPUE trend was increasing and statistically significant, we classified the stock as growing (Kleiven et al., 2022; James et al., 2004; Graham et al., 2008). We developed a standard individual interpretation of CPUE and SPR indicators (Table 1), as well as a framework for their combined sequential interpretation (Table 2) where contradictory results may invoke confusion.

2.9. Fishing vessel yield estimates by fishing gear and vessel size

The Indonesian Ministry of Marine Affairs and Fisheries (MMAF) estimates fishing vessel yield values (t/GT/year) to define the production of fishing gears and to set the appropriate taxes for fishing permits (Ministerial Decree, 2021). To compare the MMAF estimates with those derived from the analyzed CODRS dataset, we calculated the annual fishing vessel yield values for the main fishing gears of the deep-slope demersal fisheries, i.e., droplines and longlines, as well as for the different fishing vessel sizes (Nano: GT $\leq$ 5; Small: 5 $<$ GT $\leq$ 10; Medium: 10 $<$ GT $\leq$ 30; Large: GT $>$ 30). We also recalculated MMAF yield using only the species typically caught in these fisheries.

3. Results

Through a species-association approach, the model identified the same number of total fishing trips that share characteristics in terms of species composition and fishing gear (Supplementary Table S3). Fishing trips that targeted all five studied species using droplines shared the same catch composition in terms of species presence/absence. Similarly, fishing trips that targeted *L. malabaricus*, *P. multidens*, and *P. typus* using longlines shared the same catch composition in terms of species presence/absence. Despite similarities in catch characteristics within the same fishing gears, delta-GLM modelling results showed that CPUE for each species-fishing gear complex was affected by different combinations of predictors that reduced variance and minimized AIC (Table 3; Supplementary Table S4). The best fit binomial (the probability of encountering a species) and lognormal (CPUE of fishing trips where the target species is encountered) models of each species-fishing gear complex also comprised of different combinations of predictors indicating different fishing and environmental variables that determined a successful catch and the CPUE. The best fit model for dropline CPUE of *P. multidens* included depth, but depth was removed in the best fit model for *L. malabaricus* (Supplementary Table S4b, S4f). We found that FMA was a significant predictor of the CPUE ($p < 0.05$), except for the lognormal (CPUE of fishing trips where the target species is encountered) models of *L. malabaricus*-longline and *A. rutilans*-dropline, while it could not predict the probability of catch for droplines (Supplementary Table S4). Month was a significant predictor ($p < 0.05$) for the lognormal component of the model of *L. malabaricus*-longline catches (Supplementary Table S4d). Year (2016–2021) was a significant predictor for most of the binomial (the probability of encountering a species) models except for a few cases in which it was significant only for certain year(s) (Supplementary Table S4). The species-fishing gear

Table 3
Nominal, standardized, and normalized-standardized catch per unit effort (CPUE; kg/fishing days) and spawning potential ratio (SPR) of Lutjanus malabaricus (dropline and longline), Pristipomoides multidens (dropline and longline), P. typus (dropline and longline), L. erythropterus (dropline), and Aphareus rutilans (dropline) in 2020 at different fishing grounds (FMA: fisheries management area).

Fish Species	Fishing Gear	Year	Normalized CPUE	Nominal CPUE	Standardized CPUE	Longitude	Latitude	SPR (%)	FMA
Lutjanus malabaricus	Dropline	2020	0.87	0.62	1.73	107.12	3.34	3	711
			0.89	0.62	2.59	114.23	-5.18	5	712
			0.81	0.62	0.00	117.78	-1.31	11	713
			0.81	0.62	0.00	124.89	-5.96	13	714
			0.89	0.62	2.46	132.00	-2.86	3	715
			0.81	0.62	0.00	132.00	-7.51	7	718
Lutjanus malabaricus	Longline	2020	0.62	0.52	2.31	125.65	-10.94	6	573
			0.62	0.52	2.07	109.44	4.64	3	711
			0.62	0.52	2.52	116.64	-7.23	11	713
			0.62	0.52	1.99	131.06	-7.97	13	714
			0.62	0.52	2.27	125.65	3.90	0	716
Pristipomoides multidens	Dropline	2020	1.13	0.55	0.04	101.79	-4.41	6	572
			1.13	0.55	0.30	107.12	3.34	5	711
			1.13	0.55	0.32	114.23	-5.18	22	712
			1.13	0.55	0.04	117.78	-1.31	30	713
			1.13	0.55	0.02	124.89	-5.96	16	714
			1.13	0.55	0.32	132.00	-2.86	11	715
			1.13	0.55	0.05	132.00	-7.51	11	718
Pristipomoides multidens	Longline	2020	0.94	0.80	3.00	105.83	-5.75	6	572
			0.94	0.80	3.04	125.65	-10.94	11	573
			0.94	0.80	2.94	109.44	4.64	5	711
			0.94	0.80	3.10	116.64	-7.23	30	713
			0.94	0.80	2.89	131.06	-7.97	16	714
Pristipomoides typus	Dropline	2020	0.74	0.39	0.32	96.46	3.34	7	572
			0.74	0.39	0.33	107.12	3.34	4	711
			0.74	0.39	0.33	114.23	-5.18	11	712
			0.74	0.39	0.32	117.78	-1.31	11	713
			0.74	0.39	0.32	124.89	-5.96	8	714
			0.74	0.39	0.33	132.00	-2.86	11	715
			0.74	0.39	0.33	132.00	-7.51	15	718
Pristipomoides typus	Longline	2020	1.40	1.64	0.82	96.82	3.16	7	572
			1.40	1.64	0.34	125.65	-10.94	9	573
			1.40	1.64	0.78	109.44	4.64	4	711
			1.40	1.64	0.15	116.64	-7.23	11	713
			1.40	1.64	1.00	131.06	-7.97	8	714
Lutjanus erythropterus	Dropline	2020	1.50	0.61	0.48	107.12	3.34	2	711
			1.49	0.61	0.32	117.78	-1.31	8	713
			1.50	0.61	0.48	132.00	-2.86	23	715
			1.50	0.61	0.35	132.00	-7.51	100	718
Aphareus rutilans	Dropline	2020	1.27	0.92	1.94	96.46	3.34	7	572
			1.27	0.92	1.93	117.78	-1.31	10	713
			1.27	0.92	1.84	124.89	-5.96	8	714
			1.28	0.92	2.20	132.00	-2.86	4	715

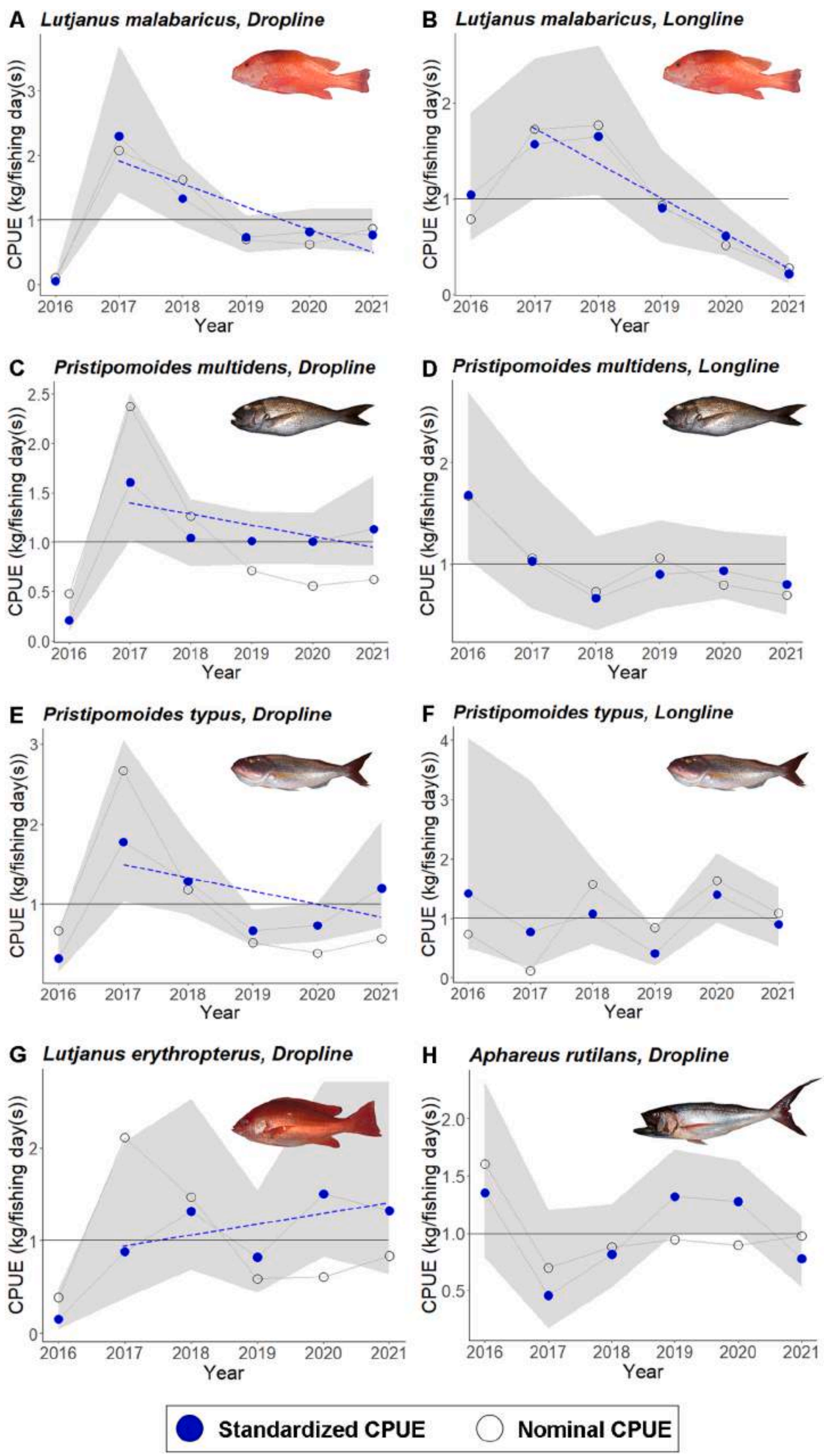

Fig. 3. Annual normalized-nominal and normalized-standardized catch per unit effort (CPUE; kg/fishing days) of eight species-fishing gear complexes of the Indonesian deep demersal fisheries. Blue circles represent standardized CPUE, while white circles represent nominal CPUE; grey shade denotes the 95% confidence interval. CPUE indices above the straight black line are larger than the mean, while indices below the black line are lower than the mean. Dashed blue lines represent linear regressions; for summary statistics of the models please refer to Supplementary Table S5.

complex in this model with the lowest D^2 and adjusted D^2 was *A. rutilans*-dropline (binomial model) (1.08%; 0.92%), while the highest was *P. typus*-dropline (lognormal model) (58.97%; 54.84%) (Supplementary Table S4j, S4o).

The standardized CPUE trends over the analyzed six years fluctuated differently among the studied species-gear complexes (Fig. 3). Notably, the standardized CPUE values for *L. malabaricus*-longline (Fig. 3B) exhibited a significantly decreasing trend (adjusted $R^2 = 0.9$, $p < 0.01$) from 2017 to 2021 (the year 2016 was excluded from the regression as an outlier). Similarly, the standardized CPUE followed a declining trend from 2017 to 2021 for *L. malabaricus*-dropline (adjusted $R^2 = 0.6$, $p = 0.07$), *P. multidens*-dropline (adjusted $R^2 = 0.2$, $p = 0.28$), and *P. typus*-dropline (adjusted $R^2 = 0.1$, $p = 0.29$); however, these trends were not statistically significant (only marginally for *L. malabaricus*-dropline) (Fig. 3A, C, E). The standardized CPUE for *L. erythropterus*-dropline (Fig. 3G) showed a marginally non-significant increasing trend (adjusted $R^2 = 0.5$, $p = 0.07$) from 2017 to 2021 (the year 2016 was excluded from the regression as an outlier). For the species-gear complexes *P. multidens*-longline, *P. typus*-longline, and *A. rutilans*-dropline, the standardized CPUE followed an undetermined trend, or was stable

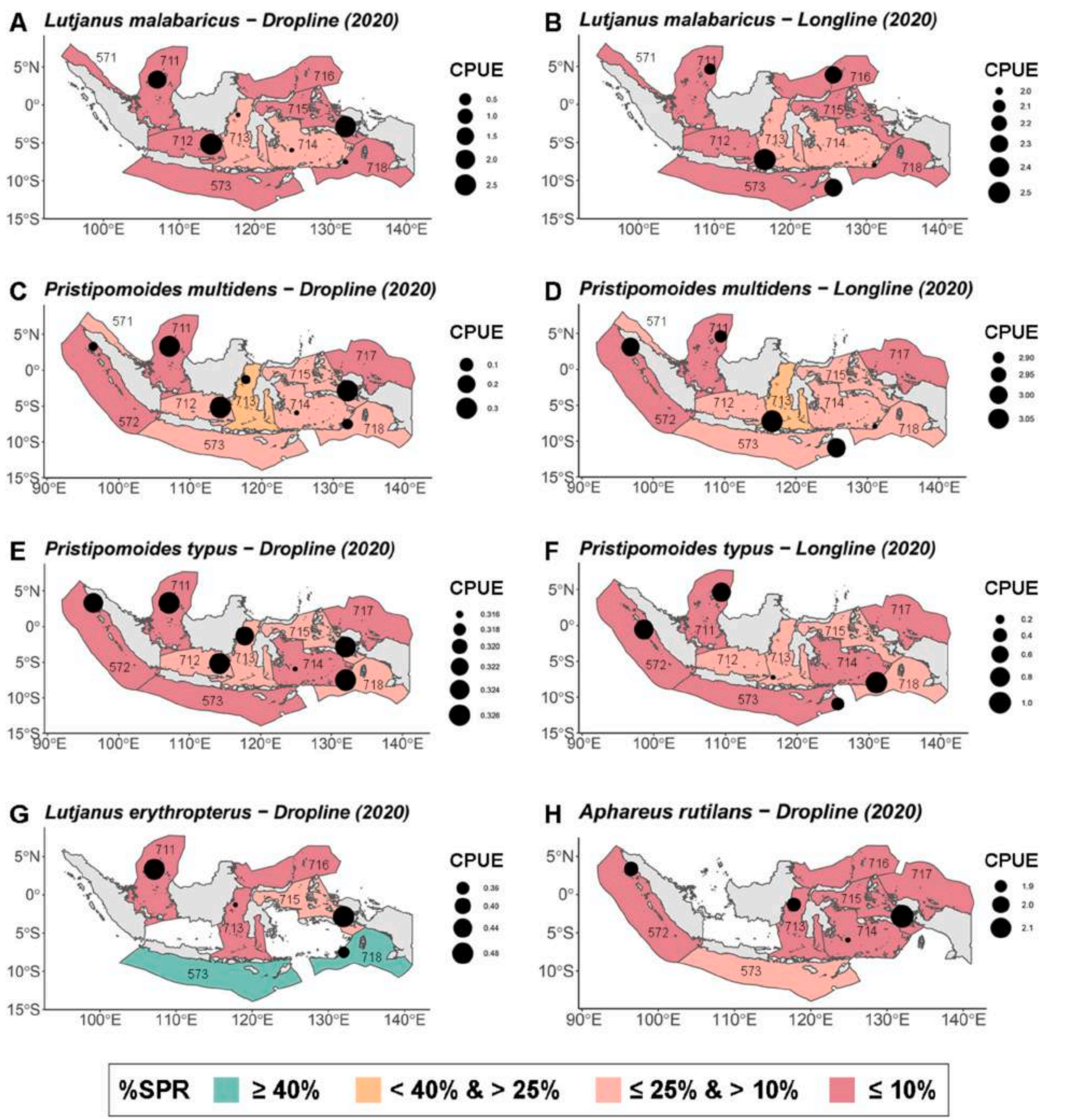

Fig. 4. Comparison between the standardized catch per unit effort (CPUE; kg/fishing day) and SPR (%) calculations in each FMA. Each circle represents a prominent fishing ground for each species-fishing gear complex. The size of the circle is scaled to the standardized CPUE index; higher CPUE values are depicted with a larger circle. Numbers represent Fishery Management Areas (FMA), delineated by black lines. FMAs with no SPR values indicate low sample sizes ($n < 50$). SPR is color-coded based on the risk level: high risk ($SPR \leq 10\%$) is dark red and light red ($SPR \leq 25\%$ & $> 10\%$), medium risk ($SPR < 40\%$ & $> 25\%$) is orange, and low risk ($SPR \geq 40\%$) is green.

through time (Fig. 3D, F, H; Supplementary Table S5).

The comparison between the standardized CPUE index and SPR showed that increasing or high CPUE indices for a species-fishing gear complex did not equate to higher SPR values (≥40% i.e., low risk or even 25–40% i.e., medium risk) (Fig. 4). Only for *P. multidens*-longline did the highest standardized CPUE (3.10 kg/fishing day) coincide with the highest SPR (30%, i.e., medium risk) in FMA 713 (Fig. 4D). On the other hand, in most cases a higher relative CPUE value was found in FMAs with a very low SPR (≤ 10%), e.g., *L. malabaricus*-dropline in FMA 712 (Fig. 4A), *L. malabaricus*-longline in FMAs 573 and 716 (Fig. 4B), *P. typus*-longline in FMA 714 (Fig. 4F), and *A. rutilans*-dropline in FMA 715 (Fig. 4H). These discrepancies between CPUE and SPR levels can be translated into different management recommendations, depending on the management priority (Table 2). Temporal trends in CPUE and SPR by species-gear complex and by FMA are given in Supplementary Figs. S1 and S2.

The fishing vessel productivity estimates (t/GT/year) provided by the MMAF for longlines and droplines are presented in Table 4, while the respective values derived from the analyzed CODRS dataset are given in Table 5 for the two gears and in Table 5 for the different fishing vessel sizes (Nano: GT ≤ 5; Small: 5 < GT ≤ 10; Medium: 10 < GT ≤ 30; Large: GT > 30). The two estimates for droplines were closer to each other - 0.7 t/GT/year the MMAF value vs 0.5 (± 0.05) the CODRS value, while the MMAF value for longlines (0.8 t/GT/year) was more than two times higher than the respective CODRS value (0.36 ± 0.04 t/GT/year). However, when only taking into consideration the taxa that are typically found in the studied deep demersal fisheries for the MMAF values, the estimates are indeed closer, i.e., (for droplines it was 0.43 t/GT/year the MMAF value vs 0.5 (± 0.05) the CODRS value, while for longlines it was 0.32 t/GT/year the MMAF value vs 0.36 (± 0.04) the CODRS value). The mean productivity of the nano vessels was the highest (0.74 ± 0.11 t/GT/year), while it was the lowest for large vessels (0.33 ± 0.05 t/GT/year). The year 2020 seemed to be the most productive year across all vessel sizes (0.68 ± 0.14 t/GT/year)..

4. Discussion

In a data-limited context where traditional age-based stock assessments cannot be implemented, such as the case of the Indonesian deep-slope demersal fisheries, a framework of multiple indicators (i.e., proxies for variables of interest rather than estimated quantities like biomass) interpreted together is often useful to infer stock status and inform management (Harford et al., 2021). Such indicators can be "empirical" / "model-free" derived mostly from raw data (e.g., CPUE; although models may be involved in standardizing CPUE) or "estimated" / "model-based" derived from raw data, other parameters, and data-limited stock assessment methods (e.g., SPR) (Dowling et al., 2015). Here, we use the combination of standardized CPUE and SPR indicators, derived from locally collected catch and length data, to gain insight on the status of prominent fish stocks in Indonesia. The specific steps to CPUE standardization and SPR estimation, the calculation of fishing ground-specific CPUE, and the sequential interpretation of CPUE and SPR indices to infer relative changes in fish abundance that lead to stock status, may generalize to other data-limited fisheries with only catch and length data available.

Comparison between standardized CPUE indices and SPRs of the Indonesian deep-slope demersal fishery highlighted the importance of monitoring and analyzing fisheries data using multiple indicators. Here, none of the studied stocks showed increasing or stable CPUE trends along with high SPR values, which means that none of them appear to be healthy or sustainably exploited. Only *L. erythropterus* showed an increasing CPUE trend that was, however, not significant but rather associated with high uncertainty, and high SPR values but only in two FMAs. The combination of CPUE and SPR seems to be the most worrying for *L. malabaricus* that exhibits decreasing CPUE trends and SPR values that are consistently low across FMAs (well below 25%); strong indications that the stock is unhealthy and current fishing rates are unsustainable. The rest of the studied stocks, i.e., *P. multidens*, *P. typus*, *A. rutilans*, also appear to be unhealthy and undergoing suboptimal fishing rates with stable CPUE trends and low SPR values (only *P. multidens* has moderate SPR in FMA 713).

Table 4
Fishing vessel yield values as set by the Ministry of Marine Affairs and Fisheries of Indonesia (MMAF; Ministerial Decree, 2021) and catch composition for the main fishing gears used in the deep demersal snapper-grouper fishery, i.e., longlines and droplines. Translation of the gear names were derived from (Ministerial Decree, 2021).

Type of fishing gear (*Indonesian*)		Catch composition	Fishing vessel yield (t/GT/year)
Hooks and lines (*pancing*)	Set longlines, i.e., bottom longlines (*rawai dasar*)	Fishes (*Arius* spp. 40%, *Lutjanus* spp. 20%*, *Cephalopholis* spp.*, *Cromileptes altivelis*, *Epinephelus* spp.*, *Plectropomus* spp. 20%*, others 20%)	0.80 [0.32**]
	Handlines, i.e., droplines (*pancing ulur*)	Fishes (*Lethrinus* spp. 21%*, *Cephalopholis* spp.*, *Cromileptes altivelis*, *Epinephelus* spp.*, *Plectropomus* spp. 21%*, *Lutjanus* spp. 20%*, *Nemipterus* spp. 15%, others 23%)	0.70 [0.43**]

* Taxa that typically show up in the studied deep demersal fisheries
** Value when we only include the taxa that typically show up in the studied deep demersal fisheries

Table 5
Annual fishing vessel yield values as calculated from the CODRS dataset analyzed in the present study for the main fishing gears used in the deep demersal snapper-grouper fishery, i.e., longlines and droplines. SE: standard error.

Fishing gear	Year	Fishing vessel yield (t/GT/year)
Longlines	2016	0.35
	2017	0.24
	2018	0.33
	2019	0.44
	2020	0.48
	2021	0.29
	Mean (± SE)	**0.36 (± 0.04)**
Droplines	2016	0.50
	2017	0.45
	2018	0.43
	2019	0.52
	2020	0.73
	2021	0.39
	Mean (± SE)	**0.50 (± 0.05)**

4.1. Standardized CPUE

Through the process of CPUE standardization, we gained insight into how the Indonesian deep-slope demersal fisheries are impacting the top five target species (*L. malabaricus*, *P. multidens*, *P. typus*, *L. erythropterus*, and *A. rutilans*). Our results indicated that fishing trips targeting these species share catch characteristics. The fit of the binomial (the probability of encountering a species) and lognormal (CPUE of fishing trips where the target species is encountered) components of the delta-GLM models were different for each species-fishing gear complex. Low D^2 and adjusted D^2 values of the *A. rutilans*-dropline binomial model, which indicated poor fit, may be caused by the lack of explanatory variables

Table 6
Annual fishing vessel yield values as calculated from the CODRS dataset analyzed in the present study for the different fishing vessel sizes used in the deep demersal snapper-grouper fishery, i.e., nano - GT ≤ 5, small - 5 < GT ≤ 10, medium - 10 < GT ≤ 30, large - GT > 30. GT: gross tonnage. SE: standard error.

	Vessel size	Fishing vessel yield (t/GT/year) by year						Mean (± SE)
		2016	2017	2018	2019	2020	2021	
Nano	**GT ≤ 5**	1.06	0.62	0.40	0.71	1.07	0.59	**0.74 (± 0.11)**
Small	**5 < GT ≤ 10**	0.40	0.43	0.42	0.41	0.70	0.30	**0.44 (± 0.05)**
Medium	**10 < GT ≤ 30**	0.52	0.41	0.44	0.47	0.43	0.23	**0.42 (± 0.04)**
Large	**GT > 30**	0.27	0.20	0.28	0.38	0.53	0.30	**0.33 (± 0.05)**
	Mean	**0.56 (± 0.17)**	**0.42 (± 0.09)**	**0.39 (± 0.04)**	**0.49 (± 0.07)**	**0.68 (± 0.14)**	**0.36 (± 0.08)**	

pertinent to the target species' probability of catch. For example, the occurrence of *A. rutilans*, which is considered benthopelagic, very mobile, and has broad habitat preferences, might be dictated by other environmental variables, such as prey distribution (e.g., teleost fish, squid, pelagic urochordates) or factors that cause prey items to aggregate, such as localized upwellings, presence of shelf breaks, or seamounts (Martinez-Andrade, 2003; Genin, 2004; Mundy, 2005; Misa, 2013; Sih et al., 2019). Other D^2 values from this study were within the range of other CPUE standardization processes (13–21%), while some were higher (up to nearly 60% for *P. typus*-dropline) showing a reasonably good fit (Punt et al., 2000; Maunder and Punt, 2004; Hazin et al., 2008).

Certain values of the annual standardized CPUE index may need additional investigation. For example, the very low nominal and standardized CPUE values of *L. malabaricus*-dropline and *L. erythropterus*-dropline in 2016 may be caused by a high discrepancy between the identified fishing trips and positive fishing trips (5 out of 485 and 6 out of 485, respectively). It is unclear whether the low number of positive fishing trips are due to low occurrence of the target species or due to misidentification of fishing trips. Low occurrence of the target species may be caused by environmentally driven fluctuations in the population (e.g., recruitment failure) or localized depletions due to fishing (Planque et al., 2010). Differences in CPUE indices among fishing gears are not surprising, given that fishing gears operate in different depths and habitats (Mous et al., 2020; Wibisono et al., 2021). A more detailed method to identify relevant fishing trips that considers targeting specific size classes may be needed to improve the fishing trip identification. A sensitivity analysis using different methods to select fishing trips, such as a direct principal component approach or clustering fishing tactics, could help corroborate the findings of this study (Winker et al., 2013; Okamura et al., 2018). Lastly, because small vessels take photographs at the end of trips, some shrinkage could occur, and interpretation of these results should take this consideration into account.

Without baseline (historical) CPUE values we cannot assess whether a current CPUE value reflects high or low abundance in the water; CPUE values give the relative change in fish abundance. A time series of CPUE estimates may demonstrate changes in the abundance of the underlying stock if we assume consistency in fishing and targeting behavior, i.e., stable choice of representative fishing locations and constant gear operation, factors that the standardization process is trying to control for by filtering them out (Thorson et al., 2017). If these assumptions are not met, then CPUE could just be reflecting more or less effective fishing practices, or natural differences in fish abundance in various areas and not overall change in the stock. CPUE standardization is a valuable but still imperfect step towards removing annual variation in the data not attributable to changes in abundance; thus, results should still be interpreted in this context, while keeping in mind other possible explanations of the observed CPUE trends (Maunder and Punt, 2004). Moreover, it should also be highlighted that CPUE indicates relative abundance and not absolute abundance as in full stock assessment models along with key fisheries reference points, thus limiting the CPUE values as a stand-alone indicator of stock status.

4.2. SPR values

Low and moderate SPRs (SPR < 40%), with a high and moderate risk, indicate a fishing mortality that exceeds sustainable levels ($F > F_{MSY}$) and overall biomass that is less than the maximum sustainable yield ($B < B_{MSY}$) (Gabriel and Mace, 1999). Generally, the higher the SPR value (e.g., >60%), the less impact fishing is having on the reproductive ability of the population, while lower SPR (e.g., 25%) indicates that fishing is reducing the egg production quite a lot (Camp et al., 2021). Nevertheless, it should be acknowledged that there can be multiple potential causes for any single SPR calculation that need to be considered when interpreting the results. In particular, the removal of mature fishes due to consistently heavy fishing pressure may indeed lead to a low SPR value (Camp et al., 2021). However, a low SPR may also be anticipated when a stock has had a recent surge in recruitment and there is a disproportionate number of juvenile fishes. Or when recent fishing has been reduced and the stock is recovering with a high abundance of juveniles not being removed. Indeed, a highly variable annual recruitment results in unreliable SPR estimates (Hordyk et al., 2015). Therefore, when interpreting results from model-based indicators like SPR, one should be aware of and consider sources of uncertainty and imprecision, i.e., modeling assumptions, limitations, and pitfalls that are usually available through simulation testing (Hordyk et al., 2015; Rudd and Thorson, 2017).

4.3. Combining catch-based indicators

Using the standardized CPUE index with SPR should be more informative about fish abundance and stock status than using either of them in isolation. However, discrepancies between the standardized CPUE indices and SPR values illustrate the potential decoupling of these two indicators which could be explained by things like hyperstability or the fact that we do not have historical CPUE values before fishing intensity was high. Therefore, we utilize a sequential approach to interpreting results where SPR gives current stock status and the CPUE index gives the relative change leading to that stock status.

High CPUE indices generally allude to high fish abundance (Richards and Schnute, 1986). However, our findings of higher CPUE even when SPR levels indicated unsustainable fishing levels, may be attributed to hyperstability, which is characterized by CPUE declining at a slower rate than abundance (Hilborn and Walters, 1992). Two factors may cause CPUE hyperstability: (a) an increase of fishers' skill or technological advances, or (b) fish aggregations (Dassow et al., 2020). Though fishers can evolve in skill and technology, the time scale of this study was not long enough to detect significant effects of technological creep (Palomares and Pauly, 2019), and there had not been significant changes in fishing technology. However, the target species' ecological characteristics indicate possible hyper aggregation through close habitat associations (Maunder et al., 2006; Dassow et al., 2020). When fish aggregate, local fish density can remain high despite changes in overall abundance. This leads to a hyperstable CPUE, i.e., high CPUE levels despite lower abundance (Hilborn and Walters, 1992).

Another explanation for high CPUE with low SPR is that we do not have CPUE values before fishing intensity was high (i.e., anything pre-2016) and thus do not really know the stock status when CPUE begins. Thus, we could have relatively high CPUE with low SPR because the CPUE is low compared to what it would have been back in time before heavy fishing. Interestingly, the areas that showed evidence of relatively high CPUE indices with low SPR values were in FMAs 712 and 713, i.e., the Java Sea and Makassar Strait, are characterized by catches with high proportion of immature juvenile fishes that may indicate the presence of nursery grounds and/or overfishing (Wibisono et al., 2021). Thus, these fishing grounds seem to be highly vulnerable to growth overfishing through the targeting of aggregations and juveniles (Froese, 2004). Targeting fish aggregations has been documented to cause a 'boom-and-bust' phenomenon in which catches are initially high, but rapidly decline to very low levels with devastating economic impacts (Bush et al., 2006; Clark and Dunn, 2012). Therefore, attention needs to be paid by policymakers to implement management strategies that utilize the best data available to avoid overexploitation of the immatures or dense aggregations in these fisheries.

4.4. Management implications

Currently, Indonesia uses two fisheries management tools. The latest official MMAF stock assessments estimate a sustainable potential yield of 12.5 million tonnes for all fisheries in Indonesia (Ministerial Decree 50, 2017). Based on the stock assessment results, the reinforcement of fisheries controls involves a licensing system in which fishing licenses are granted to fishing vessels depending on their GT and resulting yield (t/GT/year; here, based on the CODRS data, the smaller the vessel, the higher the yield), and new licenses will be only given to FMAs that are not overfished, i.e., where the exploitation rate is less than 1 (Muawanah et al., 2018). The most recent yield values set by MMAF for the main fishing gears used in the deep-water demersal fisheries, i.e., droplines and longlines (Ministerial Decree 98, 2021; Table 4), are 1.4–2.4 times higher than the mean values estimated using our dataset (Table 5). This discrepancy may be attributed to a number of factors, such as differences in the methods applied or data used to estimate the productivity values (e.g., the CODRS covers only a subset of the fleet) or the annual variability in system productivity. However, the most possible explanation is the inclusion of species that are not typically part of the studied deep demersal fisheries. When excluding those (e.g., *Arius* spp., *Nemipterus* spp.) and taking into consideration only the proportion of the typical species in the catch (see asterisks in Table 4), then the MMAF yield values and the values estimated from our dataset are close to one another. In any case, it would be worth investigating if the values provided by the MMAF might be too high given the indications of poor stock status found in this and previous studies of the fisheries (Wibisono et al., 2021, 2022; Dimarchopoulou et al., 2021). The framework and combination of stock status indicators used here has great potential to be used to inform harvest control rules in Indonesia that perform better than the status quo of 80% of MSY estimates. Using CPUE and SPR as dynamic status measures to scale back fishing when stock status is deteriorating may ensure avoiding larger issues and loss of catch and revenue in the future.

Despite the importance of formulating fisheries management strategies for these fisheries, the discrepancy between CPUE and SPR could create practical difficulties in the implementation of such measures depending on priorities (economic vs. environmental). The disjunction between the relative trends in catch (high or increasing catch rates) and stock status (low SPR) may lead fishers to erroneously believe in bountiful fish stocks. As a result, the same management scenario may result in different potential reactions by fishing communities that contribute to resistance of new management strategies, a lower ability to cope with and adapt to the newly implemented strategies, and lesser recognition of such strategies (Veitayaki et al., 2003; Marshall, 2007; Tracey and Lyle, 2011; Gaymer et al., 2014; Pita et al., 2020). Without stakeholder participation and legitimization or acceptance of management systems, it is difficult for new policies to be effective (Irvin and Stansbury, 2004; Varjopuro et al., 2008; Pita et al., 2020). However, there are other factors that can enhance policy legitimacy, such as the implementation of fisheries co-management schemes, a central element of an ecosystem approach to fisheries management considered by the Indonesian Government through the MMAF (Muawanah et al., 2018), having personal relationships with related government or non-governmental workers, consistent and honest enforcement of policies, and evidence of cultural respect towards the fishing communities where the policy is being implemented (Stern, 2008). Especially in the context of the deep-slope demersal fisheries, the MMAF is developing a harvest control strategy in addition to the pre-existing fisheries management tools, i.e., the MSY and TAC systems (Ministerial Decree 123 of 2021/KEPMEN- KP 123/2021). The Decree mandates the MMAF specifically to conduct stock assessments on these fisheries in each FMA. The present work would greatly enhance the capabilities of civil society, non-governmental organizations, the private sector, or other researchers to be more actively involved in commenting on and discussing the draft harvest control strategy in online MMAF sessions that gathers inputs on the draft.

Despite the challenges that may arise from implementing management strategies in the deep demersal fisheries, sustainable management is still feasible. For example, to prioritize short-term economic gains, protecting low or decreasing CPUE fishing grounds in either a low or high risk (high or low SPR) FMA might yield higher potential social acceptance than protecting high or increasing CPUE fishing grounds. Of course, fishers' willingness to explore alternative fishing grounds will also be affected by costs to operate in other areas and opportunities elsewhere. However, even despite the lack of potential social acceptance, high risk (low SPR) FMAs remain a high priority for fisheries management to ensure stock sustainability and long-term economic viability of the fisheries.

4.5. Conclusions

SPR and CPUE indices each have their own strengths and weaknesses. SPR's main strength is the built-in reference point of the unfished stock status, while its main drawback is that it can be misleading with a tendency to reflect recent (not long term) variability in recruitment or fishing pressure. When taking into consideration CPUE's own drawbacks, such as hyperstability and the inability to know CPUE back before fishing was heavy, the sequential interpretation of CPUE trends can benefit from SPR as a complementary measure as shown in this work. In addition to CPUE and SPR, future studies can potentially include other indicators to be tested and incorporated into these fisheries' assessments. For example, upper-length (upper 5% of the length-frequency distribution) for the swordfish fishery in Australia was a better indicator than (an unstandardized) CPUE (Punt et al., 2001). In addition, size-based indicators such as mean length of the catch (L_{mean}) or maximum size in the catch (L_{max}) may be tested as fishing typically truncates the biomass at large sizes (Ault et al., 2014; Dimarchopoulou et al., 2018). The CPUE index can also be utilized in subsequent fisheries modeling to estimate fishing mortality (i.e., catch-and-effort-time-series) or as an index of abundance to fit fisheries models using the observation error method (Maunder and Starr, 2003; Ault et al., 2014). With the addition of other fisheries indicators, more research will be needed into the hierarchical decision-making to summarize potentially opposing fishery indicators (Wilson et al., 2010; Dowling et al., 2015; Harford et al., 2021).

Used together to complement one another, the standardized CPUE indices and SPR allow policymakers to achieve a more holistic view of fisheries. CPUE trends and SPR values give a clearer picture of the stock status than either of them alone. The standardized CPUE index alone would not be particularly informative for management because of the lack of baseline values to compare the current values with and it could give a misleading conclusion of fisheries performance (Maunder et al., 2006). However, SPR without the CPUE indices is not able to detect the occurrence of possible fish aggregations or be definitive about stock status owing to recent changes in recruitment or fishing pressure. Our results suggest that despite the varied usage of CPUE in past fisheries management scenarios, when combined with other fisheries indicators such as SPR, the fisheries-dependent index remains an asset in determining fisheries status. The difference between CPUE and actual fisheries sustainability is a perception divide that requires public engagement and trust-building between policymakers and fishing communities.

CRediT authorship contribution statement

Donna Dimarchopoulou: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Elle Wibisono:** Conceptualization, Methodology, Formal analysis, Writing – original draft. **Steven Saul:** Methodology, Writing – review & editing. **Paul Carvalho:** Methodology, Data curation, Writing – review & editing. **Angga Nugraha:** Methodology, Writing – review & editing. **Peter J. Mous:** Conceptualization, Methodology, Writing – original draft, Funding acquisition, Project administration. **Austin T. Humphries:** Conceptualization, Methodology, Resources, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition, Project administration.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fishres.2023.106854.

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