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Impact of climate variability on moonfish (*Mene maculata*) catch rate in the waters off southwestern Taiwan

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Abstract

A commercially significant small coastal forage fish, moonfish (*Mene maculata*), accounts for almost 98% of Taiwanese purse seine capture, primarily in the southwestern Taiwan region. Research indicates that climate indices affect coastal fish catch and dispersal, while the link between moonfish and climatic variability in this region is still unclear. This study found that the delayed period of Pacific Decadal Oscillation (PDO), North Pacific Oscillation (NPO) and North Pacific Gyre Oscillation (NPGO) affect moonfish distribution and catch rates off southwestern Taiwan. Understudied are the environmental factors connected to these oscillations and their delayed consequences on moonfish catch rates. We focussed on Taiwan purse seiner capture rates (catch per unit effort or CPUE) of moonfish in southwestern Taiwan from 2014 to 2020 and delayed oscillation occurrences up to 5 years to better understand these processes. CPUE demonstrated a 3 to 4-year positive connection ($r > 0.5$) with NPGO, NPO and PDO. The region's moonfish catch rates were most affected by NPGO with a 4-year lag, followed by a 3-year lag of PDO and lastly a 4-year lag of NPO, according to the results of generalized additive models (GAMs). All the three oscillations had the greatest impact on moonfish catchability when a lag of >2 years was present. Between 2014 and 2020, moonfish CPUE fluctuated, peaking in 2019. The climatic parameters that affect moonfish in southwestern Taiwan and the Taiwanese purse seine fisheries catches are shown by this study.

KEYWORDS
catch per unit effort, moonfish, NPGO, PDO, time series

1 | INTRODUCTION

Climate oscillations, anomalies and shifts affect marine ecosystem biological processes and species abundances and distributions (Tian et al., 2008). Climate variability, as extensively documented in scientific studies (Báez, Muñoz-Exposito, et al., 2019b), can impact various aspects of small pelagic fisheries, including species phenology, abundance, distribution, recruitment, catchability, physical condition and fishing effort (Báez, Santamaría, et al., 2019a). Climatic events like the El Niño Southern Oscillation (ENSO) in the Pacific Ocean and the North Atlantic Oscillation (NAO) in the Atlantic Ocean can impact pelagic and coastal species populations, sometimes with bidirectional effects (Wieners et al., 2017). The ENSO, impacting the marine community, is also associated with alterations of oceanographic conditions like the sea surface temperature (SST) (Mondal & Lee, 2023). Others like Pacific Decadal Oscillation (PDO) and the North Pacific Gyre Oscillation (NPGO) affect indices like adult recruits per spawner, smolt and fish catches (e.g. Malick et al., 2017), which in turn affect abundance and catchability of commercially important fish species (Báez & Real, 2011).

Managers need to grasp the key drivers of coastal fish dynamics due to potential impacts on societies relying on them, necessitating effective population management (Leitão, 2015). Climate variability might also influence fish market pricing (Fernández et al., 2020). The ENSO triggers irregular SST fluctuations known as La Niña and El Niño, with episodes influenced by the Southern Oscillation Index (SOI) associated with atmospheric oscillations, determined by pressure differentials between Tahiti and Darwin weather stations (Yan et al., 2011). To enhance ENSO understanding, scientists recommend replacing the SOI and Niño-3.4 indices with the multivariate ENSO index (MEI), which provides a more comprehensive representation of ENSO (Mazzarella et al., 2013).

Physical factors, such as atmosphere–ocean interactions that cause aberrant North Pacific SST patterns, affect the PDO (Newman et al., 2016). Wang et al. (2014) revealed that PDO-ENSO interactions influence dry-wet patterns in the Pacific Ocean. NOAA's Climate Prediction Centre (CPC) relies on the Oceanic Niño Index (ONI) to monitor tropical Pacific Ocean SSTs and predict El Niño events. Calculated from 3-month running means (3-MRMs) in the Niño 3.4 region, the ONI serves as a key indicator. Additionally, the NPGO, representing the second mode of sea surface height anomalies (SSHa), plays a pivotal role. Di Lorenzo et al. (2008) demonstrated its impact on salinity, nutrients and chlorophyll-a levels. Moreover, they established a correlation between the NPGO index and variations in salinity, nitrate and Chl-a concentrations, indicating its link to shifts in upwelling-favourable winds. The oceanic expression of NPGO is tied to the North Pacific Oscillation (NPO), an atmospheric mode discovered by Sir Gilbert Walker in 1924. This pattern encompasses a north–south sea level pressure (SLP) gradient across the North Pacific, influencing wintertime storm tracks (Linkin & Nigam, 2008). Interestingly, the Western Pacific (WP) mode, a north–south dipole in the western-central Pacific basin, parallels the NPO's variability. The NPO serves as an indicator of the SLP manifestation of the WP geopotential height pattern (Nigam & Baxter, 2015). Decadal investigations have delved into NPO variability and central Pacific SST fluctuations, particularly during El Niño events (Di Lorenzo et al., 2013).

Early investigations with a single explanatory variable showed that oscillations delayed by 4 to 5 years improved outcomes, confirming their linear impact (Báez et al., 2020). Faillettaz et al. (2019) found a 16-year AMO-NAO effect in Atlantic bluefin tuna. Another research by Robinson et al. (2010) indicated that climatic variability may affect a fishing-dependent economy. The results have managerial implications. However, the influence of such oscillations on this matter has not been extensively investigated. Therefore, lags of climatic oscillations are effective forecasters.

Southwestern Taiwan waters (STW) are a major western Pacific Ocean fishing region between Taiwan and China. It is an important waterway between the South China Sea (SCS) and East China Sea (ECS). It allows water and chemical transfer along Taiwan's west coast. This region's unique bottom topography affects the monsoon and convergence of numerous current systems, affecting biogeochemical, physical and biological processes (Tseng et al., 2020). Three primary currents—China Coastal, Kuroshio Branch and SCS—influence STW. Currents affect global ocean circulation and climate variability with several effects. The China Coastal Current (CCC), Kuroshio Current (KC) and Kuroshio Branch Current (KBC) have a significant impact on the waters of STW, leading to a rich biodiversity and high productivity in this area (Hobday & Pecl, 2014). The oceanographic conditions of STW are influenced by seasonal monsoons and variable terrain, which have a significant impact on these currents (Lan et al., 2020). The Taiwan Strait (TS) plays a crucial role as a migratory pathway for numerous fish species, impacting ecosystem dynamics as well as biogeochemical and physical processes (Tseng et al., 2020). Several species of finfish utilize the STW for spawning, feeding and overwintering (Ju et al., 2020). Taiwan's coastal waters possess unique characteristics that enhance their abundant and diverse fisheries resources, rendering them a highly profitable fishing location (Hsiao et al., 2021).

The major distribution of *Mene maculata*, the only species from Menidae family commonly called the moonfish (Feng et al., 2012) in Taiwan, is concentrated in the deeper coastal regions of the STW (21-25°N and 117-122°E). The species possesses a slender, flat and thin body with a pointed breast. The appearance of the moonfish is characterized by a light blue colour on the upper side of its dorsum and a silvery white colour on its body (Nguyen et al., 2021). Living at depths of 20–100 m, this thin Indo-Pacific coastal forage fish has become economically important in Taiwan as an edible fish. Along with lobsters, shrimps and cephalopods, moonfish is an important commercial fish. This species is mainly found in the fishing grounds between Tainan and Pingtung. It exhibits photo-taxis and engages in spawning migration. While torch-light fisheries primarily capture moonfish, with fishing activities occurring throughout the year, the main fishing season in the STW spans from October to April of the subsequent year. During this period, the main fishing location accounts for over 90% of the total moonfish catch in Taiwan (Nguyen et al., 2021). Bharadhirajan et al. (2014) highlighted that the tissue of *M. maculata* contains high-quality protein and a well-balanced composition of amino acids. Additionally, this species has the highest levels of calcium and other minerals. Consequently, they suggested that *M. maculata* could be a valuable food source for human consumption. Moonfish, as small forage fish, plays a crucial role in transferring energy to apex predators like marlins, dolphinfish and tunas (Lan et al., 2012). There is a significant correlation between the biomass of forage fish and the biomass of their predators and prey. Pikitch et al. (2014) found a correlation between a decline in forage fish biomass and an increase in jellyfish and squid biomass. The energy density and nutritional quality of forage fish tissue can impact predators as well. These small forage species like moonfish are highly fragile, with high mortality rates and increased vulnerability of their eggs and larvae to predation. They are also sensitive to strict environmental conditions.

Despite rapid growth, these organisms generally have a maximum weight of <500 g and a short lifespan. Moreover, excessive reduction or exploitation can lead to a decline in the average lifespan of these individuals (Gaerlan et al., 2018). Coastal fish species like *M. maculata* are particularly sensitive to environmental changes, and this sensitivity can be exacerbated by climate variability. This sensitivity has significant implications, as it can result in a chain reaction of impacts across the food web. These effects are mainly due to their large biomass at intermediate trophic levels and their ability to regulate the food web through wasp-waist control (Albo Puigserver et al., 2018). STW moonfish catchability may depend on ecosystem elements including food and feeding, habitat, physical environment and climate trends. Rivai et al. (2018) suggest that SST, SSH, sea surface current and sea surface salinity (SSS) are important physical factors that can be used to determine the spawning and feeding habitats as well as the distribution of coastal or pelagic fish. Coastal regions with upwelling waters often display increased chlorophyll concentrations. Nutrient concentrations, such as nitrogen (N), phosphorous (P) and silicon (Si), contribute to high chlorophyll levels. While moonfish, being a small coastal fish, may not have a direct association with primary productivity, regions characterized by fluctuating primary productivity can have diverse impacts on this species. SST plays a vital role in regulating body temperature and reducing heat loss (Phillips et al., 2014). Numerous studies have examined the associations between growth or metabolism and environmental factors. Environmental factors, including dissolved oxygen levels, salinity, daily feeding period, food quality and pollutants, play a crucial role in determining species distribution. Dissolved oxygen is a crucial factor affecting fish growth. The presence of adult zooplankton is expected to have a positive effect on the growth rate of older moonfish larvae. Another possible reason for the inconsistent temporal effects could be the changing population structure of these species over time (Albo Puigserver et al., 2018). Hence, understanding the environmental impact on moonfish is crucial.

The coastal and offshore fisheries in the region have experienced substantial growth since the 1950s, leading to a significant rise in production. The highest level of production was reached in the 1980s, with an annual output surpassing 400,000 t. The offshore and coastal fisheries in Taiwan declined due to the impact of World War II. Before 1980, the proportion of coastal and offshore fisheries production relative to overall fishery production declined due to the rapid growth of pelagic fishing. Starting around 1975, Taiwan's coastal moonfish harvest has fluctuated. Overexploitation peaking in the 1980s after steady increase from the 1950s caused a fall in moonfish catches after the 1990s (Liao et al., 2019). Following this, there was a gradual decline in catches, which coincided with an increase in deep-sea fishery catch. The coastal fisheries in Taiwan hold significant social, cultural and food security importance. However, the economic significance of these coastal fisheries is often underestimated. Another factor is the historical marginalization of small-scale fisheries (SSFs) and the belief that they are insignificant in terms of catch and importance. Fishing villages in Taiwan may rely more on coastal and near-coastal resources. There is a potential for an increase in the reliance of fishing communities in Taiwan on coastal and near-coastal resources in the future. This is due to the anticipated negative impact of climate change on coastal resources in the Pacific region (Bell et al., 2011). Global warming-induced climatic variability may have altered moonfish harvest rates; however, there are few comparisons. Therefore, lagged influence of climatic oscillations may affect STW moonfish capture rates. Conservation and management of this marine resource need understanding these implications. The fishing industry is a source of food, animal protein and local employment (Pauly & Zeller, 2017), but SSFs have limited adaptability, rendering them susceptible to climate change (Brugère & De Young, 2015). To enhance stock management, recognizing the potential connection between climatic cycles and moonfish landings is essential. By implementing proactive restrictions, fisheries management can mitigate these processes.

In this particular context, accurately determining the species composition of the total catch poses significant challenges (Pianet et al., 2000). Scientists and managers are often concerned about the link between fish catch and abundance (Maunder et al., 2006). Effective fisheries management requires understanding catch variability and identifying the most important characteristics, including the design of vessel facilities (Barman & Bora, 2021, 2022). Multiple target species' fishing strategies may be seen in a single fishing trip, making it difficult to adjust fishing behaviour from total catch (Palmer et al., 2009). It is commonly assumed that the total fish catch index is directly proportional to the biomass. Mandatory catch return cards, logbooks and sale slips provide more accurate abundance data from fisheries-dependent catch per unit effort (CPUE; Cardinale et al., 2009). Since CPUE is simpler to calculate than abundance or density estimates and may fluctuate proportionately with abundance or density, it may be beneficial for directly monitoring populations.

Understanding how fisheries adapt to climate variability is crucial for developing sustainable exploitation techniques within the context of climate forcing and fishery management strategies aligned with the SDGs. Despite having the historical STW moonfish capture data from 1975 to 2021 (Figure S3), this research used yearly nominal catch per unit effort (N.CPUE) data from 2014 to 2020 to explore the lagged influence of climatic oscillations using regression models (Figure 1).

2 | MATERIALS AND METHODS

2.1 | Taiwanese seine moonfish catch data

The Taiwanese purse seine industrial fishery is the primary source of moonfish catch, and Taiwan heavily relies on this species. The Taiwanese purse seine fleet in the Pacific Ocean dominates moonfish catches, but these catches have gradually declined since the 1990s while deep-sea fishing increased (Figure S2). Taiwan has been granting fuel subsidies to fishing vessels since 1958 (Qiu, 2007). The subsidy amount for fishing vessels was initially determined based on the

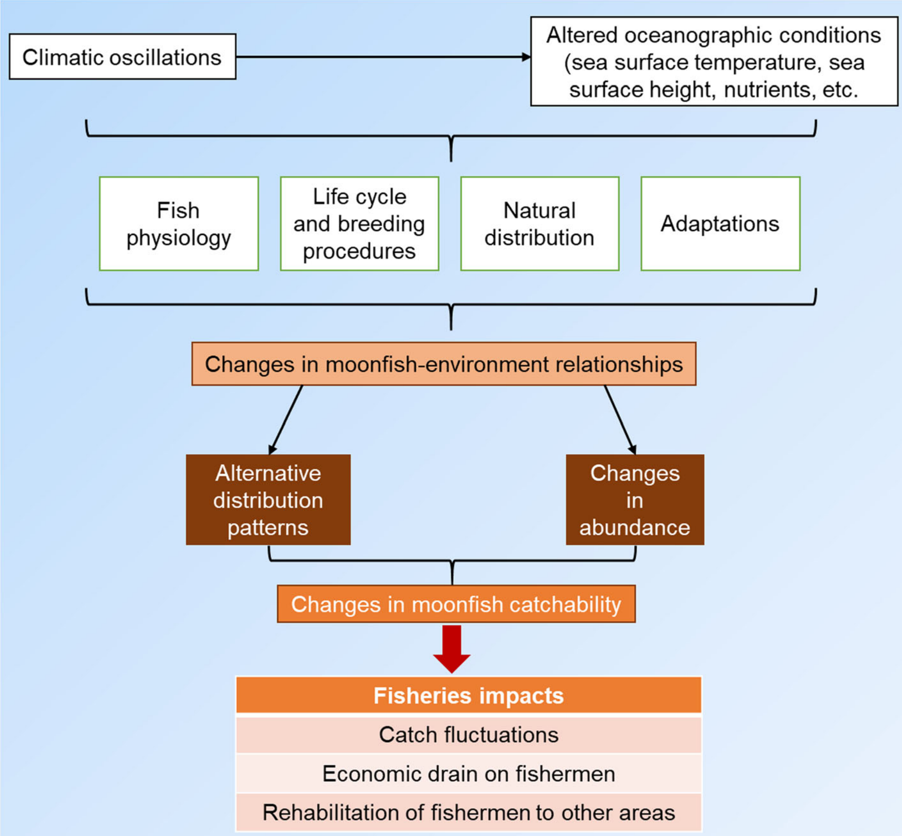

FIGURE 1 The hypothetical flowchart employed in the present study to examine the impact of climate oscillations on moonfish catch rate in the southwestern Taiwan waters (STW).

duration of time the vessel spent at sea. The evaluations are performed using 3-min interval position records obtained from low-cost customized voyage data recorders (VDRs). The Fisheries Agency (FA) of Taiwan provides financial support for the installation of Vessel Monitoring Systems (VMS) on fishing vessels that apply for fuel subsidies. If VDR data could be used to estimate fishing effort, it would enable the creation of logbook-like data similar to the one described by Chang (2014). VDRs can yield reliable information offering similar advantages in fisheries research. These benefits include estimating fishing efforts (Chang & Yuan, 2014) identifying detailed fishing areas for marine spatial planning (Jennings & Lee, 2012) and combining data from logbooks to analyse the spatial distribution of catches and effort (Gerritsen & Lordan, 2011). Vessels that utilize VDRs and regularly record and weigh their catches within a short timeframe are likely to offer more reliable catch information compared to vessels that solely rely on logbooks, which often have questionable quality. The utilization of VDRs that offer free 3-min data intervals enables the provision of adaptable assistance for conducting more accurate analyses. Therefore, the present study used a detailed moonfish catch data combined from logbook and VDR system from January 2014 to December 2020 obtained from Taiwan FA, including catch by weight, operational data and fishing effort indicators.

The high spatial resolution dataset ($0.1 \times 0.1^{\circ}$) includes information on catch, which is reported by weight depending on the fishing fleet, as well as operational data such as the number of days gone for fishing and the coordinates of the fishing areas. The duration of fishing-related activities, including searching and fishing operations such as setting, hauling and removing catches from fishing gear, can be used as a reliable indicator of fishing effort. This measure is commonly expressed as the number of fishing days or hours per boat per year. Here, the total catch was calculated by the following formula:

$$\text{Catch} = \frac{\text{Total catch weight in kg} * \text{working hours}}{\text{Total work hours}}.$$

Followed by this, the monthly N.CPUE was determined by

$$\text{N.CPUE}\left(\frac{\text{kg}}{\text{h}}\right) = \frac{\text{Catch (kg)}}{\text{Total hours}}.$$

2.2 | Climatic indices

This study aimed to investigate the cyclic variation of climatic oscillations and its impact on fisheries production in the waters surrounding STW. To achieve this, we collected data on Pacific-related climatic factors and conducted an analysis of their effects. The evaluated atmospheric climatic oscillation indices included PDO, SOI, ONI, NPGO, NPO, Niño 3.4 and MEI v2 (Table 1).

The seven climatic indices and their lags were incorporated into our explanatory analysis for this purpose. To consider the potential

TABLE 1 Sources of climatic indices used in the study.

Climatic oscillation	Abbreviation	Source
Oceanic Niño Index	ONI	https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php
North Pacific Gyre Oscillation	NPGO	https://www.psl.noaa.gov/data/correlation/npgo.data
Pacific Decadal Oscillation	PDO	https://psl.noaa.gov/data/correlation/pdo.data
Southern Oscillation Index	SOI	https://psl.noaa.gov/data/correlation/soi.data
West Pacific	WP	https://psl.noaa.gov/data/correlation/wp.data
North Pacific Oscillation	NPO	https://psl.noaa.gov/data/correlation/epo.data
Multivariate ENSO index version 2	MEI v2	https://psl.noaa.gov/enso/mei/
Niño 3.4	-	https://psl.noaa.gov/gcos_wgsp/Timeseries/Data/nino34.long.anom.data

delayed impact of climatic variables on the CPUE, we lagged the climatic indices by up to 5 years. This resulted in six variables for each climatic oscillation, totaling 42 explanatory variables. The lagged values were used as previous years' data for each index. A maximum lag of 5 years was chosen based on the duration of the fishery dataset of moonfish in the STW region.

2.3 | Examining and analysing data

The study employed autoregressive integrated moving average time series analysis to evaluate the variability of yearly N.CPUE. The analysis was conducted using the 'ts' function from the 'tseries' package in the R environment (version 4.2.3; Araveeporn & Banditvilai, 2023). The climatic indices time series were analysed using the changepoint R package (Killick et al., 2016) to identify multiple change points in the mean and variance of the time series by the 'cpt.meanvar' function in R for change point detection. This method was chosen due to its widespread usage as a multiple change point search method (Killick & Eckley, 2014).

In order to determine the factors that influence the response variable on moonfish CPUE, Pearson's correlation coefficient was initially calculated using climatic indices. It was analysed between the moonfish CPUE and climatic oscillations, including their respective lags. The analysis was conducted using the 'cor.test' function from the 'corr' package in the R environment (version 4.2.3). The formula to calculate the coefficient is as follows:

$$r = \frac{n(\sum XY) - (\sum X)(\sum Y)}{\sqrt{\left\{n\sum X^2 - \left(\sum X^2\right)\right\}\left\{n\sum Y^2 - \left(\sum Y^2\right)\right\}}}.$$

In the given context, the variables are denoted as follows: r represents the correlation coefficient, n represents the number of observations, X represents the first variable, and Y represents the second variable.

A higher correlation coefficient value indicates collinearity, with an absolute value near 0.8 often considered significant (Young, 2018). Climatic oscillations with an absolute correlation value >0.1 were chosen as potential explanatory variables with non-linear effects on moonfish. Additionally, only those lags of the chosen climatic oscillations having an absolute correlation value >0.1 were finally selected for the next step.

A variance inflation factor (VIF) was then used to measure collinearity among the chosen climatic oscillations ($r > 0.1$) and their selected lags ($r > 0.1$) in the R environment (version 4.2.3) through the 'vif' function of the '*car*' package prior to pairwise model construction by the formula below:

$$\mathrm{VIF} = \frac{1}{1 - R^2}.$$

The VIF measures the impact of independent variable correlations on the variance of regression coefficients. A VIF of 1 means no correlation, 1–5 suggests moderate correlation, while 5–10 identifies high correlation. VIF values >10 indicate severe multicollinearity (Salmerón et al., 2020).

2.4 | Generalized additive models (GAMs)

GAMs are non-parametric extensions of multiple linear regressions that relax the assumptions about the underlying statistical data distribution (Hastie & Tibshirani, 1990). The linear predictors in these models are connected to the response variables through a link function, allowing for the application of regression models to non-Gaussian response variables. According to Diankha and Thiaw (2016), GAMs employ data-driven functions like splines and local regression, which outperform the polynomial functions utilized in linear models. Zwolinski and Demer (2014) argue that these models enable the representation of intricate non-linear relationships between species and their environment.

The GAM semi-parametric smooth functions were employed to model the interactions between the climatic indices and moonfish N.CPUE. Eighteen models were adjusted with one explanatory variable. To prevent collinearity, only variables with VIF < 5 were included in the models. Zuur et al. (2009) employed the Akaike information criterion (AIC) and graphical validation of model residuals for model selection. The climatic oscillation lag variables were ranked based on their deviance explained (higher percentage is preferred) and the AIC (lower value is preferred). Only the variables with the highest deviance explained and lowest AIC were chosen for further analysis. The relationship between the catch rate and the predictor variable can be represented by the equation:

$$\text{GAM}:(\text{Catch rate}+c)\sim s(\text{Predictor variable}).$$

The N.CPUE of moonfish was analysed to determine the cumulative impacts of combinations of climate oscillations with varying delays (selected on the basis of AIC and deviance explained) using the GAM approach. Following the VIF test, GAMs were built for moonfish using these unique pairings of climate oscillation variables with the formula below:

$$\text{GAM}:(\text{Catch rate}+c)\sim s(\text{Climatic oscillation 1})+s(\text{Climatic oscillation 2}).$$

The constant value, denoted as c, is equal to 0.1. The smoothing function is represented by the variables. The data exploration and statistical analyses of GAM models were conducted using the 'mgcv' library in R (version 4.2.3; Chang et al., 2021).

2.5 | Wavelet analysis

Sang et al. (2009) outline wavelet analysis as a valuable tool for examining hydrological time series. This approach, likened to a microscope, has replaced Fourier analysis with continuous wavelet transform (CWT) and wavelet coherence (WTC) analysis due to sporadic events in geosciences (Torrence & Compo, 1998). Labat (2005) demonstrates wavelet analysis's application in geosciences, particularly in hydrology. WTC precisely identifies time intervals with enhanced periodicity, as utilized in the study comparing moonfish CPUE and climatic oscillations, following Grinsted et al.'s (2004) methodology, which incorporates findings of Torrence and Compo (1998) and Torrence and Webster (1999). The mathematical description of WTC analysis for two different time series, represented as X and Y, is as follows:

$$WC(a,\tau)=\frac{|SW_{XY}(a,\tau)|}{\sqrt{\|SW_{XY}(a,\tau).SW_{XY}(a,\tau)\|}}.$$

The symbol '·' denotes the use of smoothing. This equation represents the cross wavelet analysis of two different time series. The cross wavelet analysis involves the conjugation of two separate time series wavelet transforms by the following formula:

$$W_{XY}(a,\tau)=C_X(a,\tau)C_Y^*(a,\tau).$$

WTC analysis finds locally phase-locked correlations between time series, while cross wavelet analysis finds regions on scalograms with high common powers and indicates the phase relationship between the periods found in both time series (Grinsted et al., 2004).

3 | RESULTS

3.1 | Variability in moonfish catch

Catch estimates are employed to depict the species composition of specific fisheries, assess utilization rates, monitor quotas, estimate fishing mortality and calculate CPUE. The total capture of moonfish exhibited an upward trend from 2016 (Figure 2). However, the annual average CPUE showed fluctuations, ranging from 200 to over 800 kg/h between 2016 and 2017, followed by fluctuations in N.CPUE between 800 and as low as 800 kg/h from 2017 to 2018. There was a substantial increase from 2018 onwards up to 2020, with the highest and lowest N.CPUE observed during two periods: April to December in 2014 and 2018. A consistent decline in the average N.CPUE was noted during the winter season from 2014 to 2020. As a result, moonfish N.CPUE exhibited significant seasonal and annual variations, with notably high levels in 2017, peaking in May and June. The Taiwanese purse seine fishery in STW played a predominant role in moonfish landings, as depicted in Figure S2.

The moonfish catch exhibited a fluctuating pattern characterized by an initial increase followed by a subsequent decrease from 2017 to 2020. From 2014 to 2016, there was a noticeable upward trend in catch, reaching its peak with >4000 t in 2015. However, since 2016, there has been a clear downward trajectory, with the lowest catch recorded <500 t in 2018 (Figure 3). The N.CPUE of moonfish exhibited temporal fluctuations with a generally increasing trend throughout the study period, observed from 2014 to 2020. The trend of this line remained relatively stable prior to 2018, but experienced a significant increase starting post-2018. It reached its first peak of 500 t/h in 2015, and showed slight fluctuations between 2015 and 2017. The highest peak of around 3000 t/h was observed in 2019.

3.2 | Correlation between the moonfish CPUE and climatic indices

The N.CPUE showed the strongest negative correlation with NPGO ($r=-0.25$), followed by a weak positive correlation with NPO ($r=0.12$) and a weak negative correlation with PDO ($r=-0.11$; Table 2).

The Pearson correlation coefficient value (r) for NPGO, NPO and PDO were >0.1. Thus, these three climatic oscillations were chosen for further experimentation. There was no multi-collinearity detected among NPGO, NPO and PDO as their VIF values were near 1 (Figure 4).

3.3 | The trend between climatic factors and catch rate variations of moonfish

The highest N.CPUE in 2019 coincided with the lowest NPGO index value whereas PDO and NPO showed an opposite trend (Figure 5). Positive NPGO index values coincided with the lowest values of N.

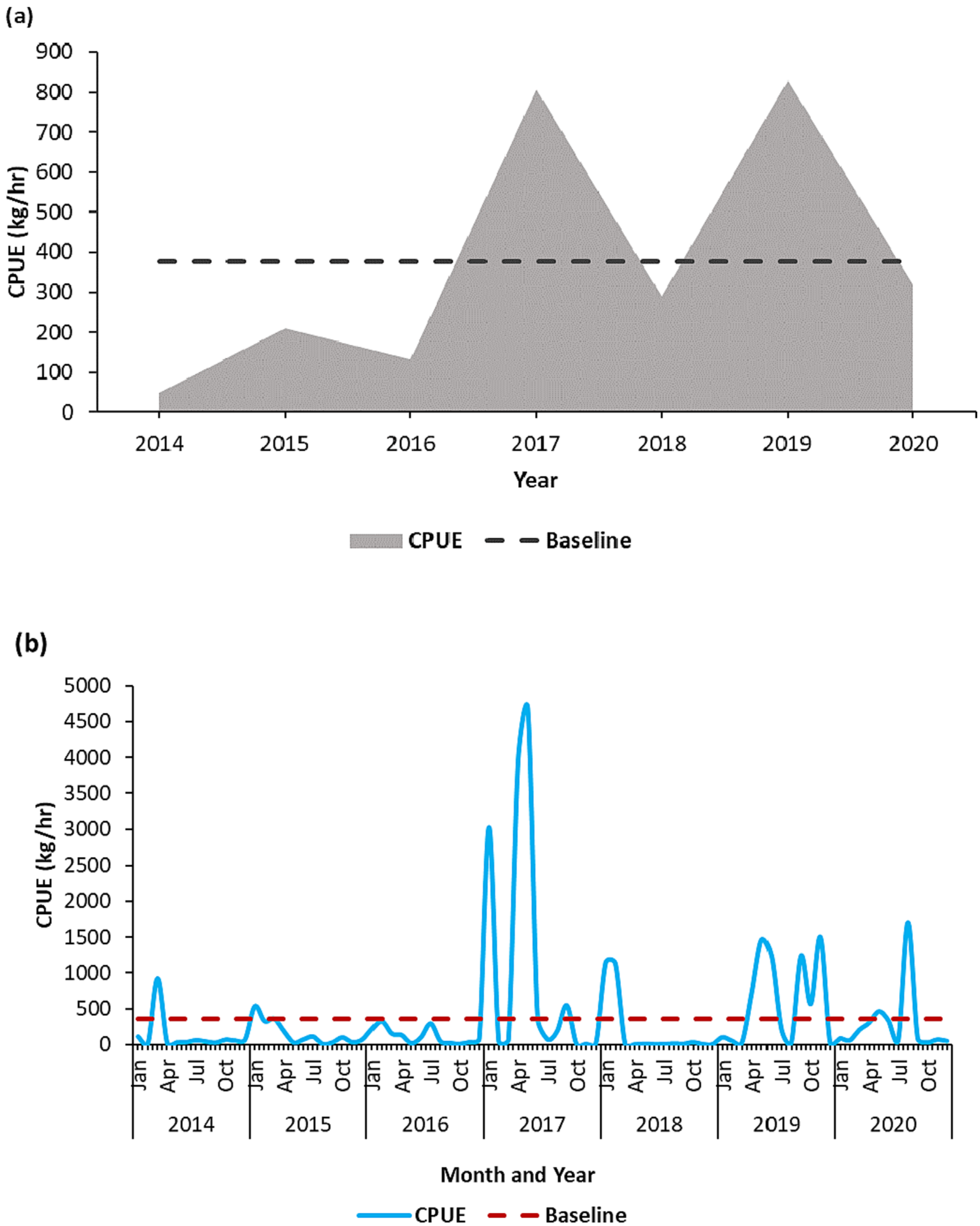

FIGURE 2 (a) The annual time series data for the average nominal catch per unit effort (N.CPUE; in kg/h) of moonfish (*Mene maculata*) between 2014 and 2020 is shown. (b) The moonfish N.CPUE in the southwestern Taiwan waters (STW) from January to December between 2014 and 2020, as reported by the Taiwanese purse seine fishery, is presented. The data includes the number of working hours conducted by fishermen at the main landing sites.

CPUE, such as the least N.CPUE in 2014 and 2016, which coincided with the highest values of the index (Figure 5). For PDO, there was a positive trend in 2019 where high N.CPUE was recorded with positive PDO index. On the contrary, the strongest PDO values from 2014 to 2016 were associated with very less N.CPUE, particularly in those years. NPO also displayed a similar trend like PDO where the highest

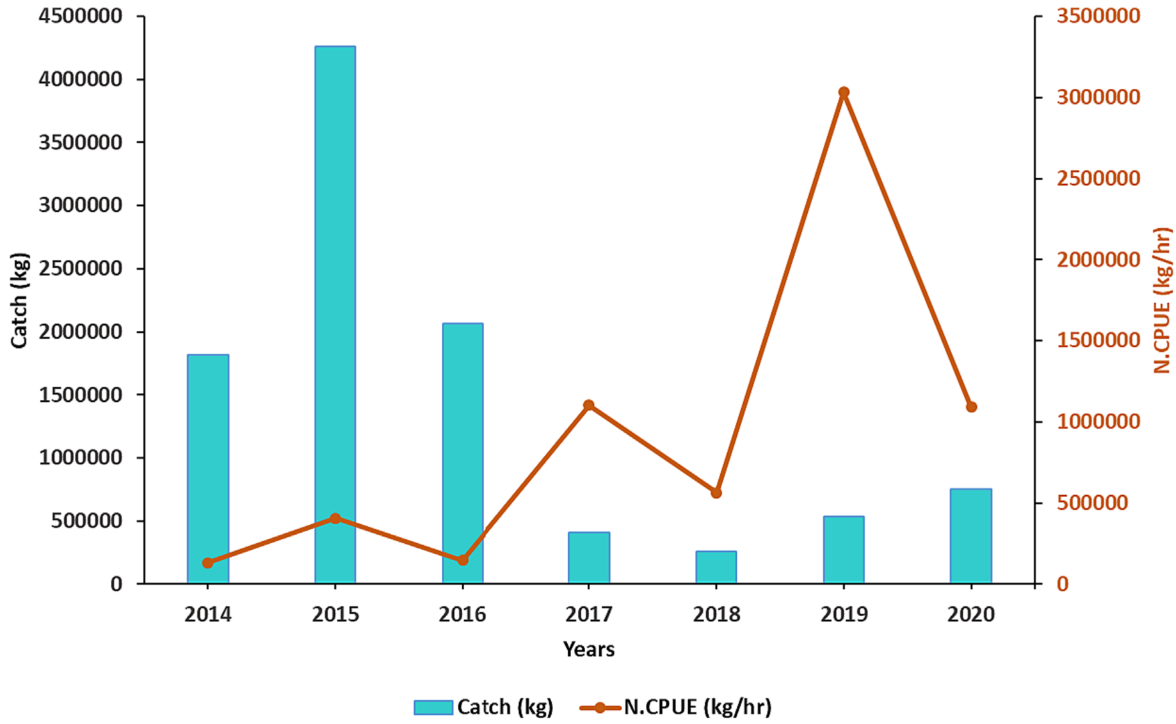

FIGURE 3 The temporal variations of moonfish in the study area from 2014 to 2020. The graph displays the temporal fluctuations in moonfish catch (represented by the blue lake bar) and nominal catch per unit effort (N.CPUE; indicated by the bright orange line).

TABLE 2 Correlations between N.CPUE and climatic index.

Variable 1	Variable 2	Pearson correlation coefficient (r)
N.CPUE	ONI	−0.09
	NPGO	**−0.25**
	PDO	**−0.11**
	SOI	−0.08
	WP	0.01
	NPO	**0.12**
	MEI v2	−0.08
	Niño 3.4	−0.08

Note: The correlation coefficients with absolute values >0.1 are highlighted in bold.
Abbreviations: MEI v2, multivariate ENSO index version 2; N.CPUE, nominal catch per unit effort; NPGO, North Pacific Gyre Oscillation; NPO, North Pacific Oscillation; ONI, Oceanic Niño Index; PDO, Pacific Decadal Oscillation; SOI, Southern Oscillation Index; WP, West Pacific.

N.CPUE on 2019 occurred with a positive NPO index whereas the N. CPUE were minimal during the positive NPO years from 2014 to 2016.

3.4 | Correlation between lags of climatic indices and N.CPUE variations of moonfish

The Pearson correlation coefficient analysis showed that there was significant correlation between the lags of the three selected climatic oscillation: NPGO, NPO and PDO with the N.CPUE of moonfish (Table 3). Almost all the lags of the three oscillations had a significant impact on the N.CPUE of moonfish, except the 0- and 2-year lag of NPO. The most pronounced negative correlation (r = −0.7) was observed only between the 0-year lag of NPGO and the moonfish N. CPUE. Conversely, the strongest positive correlation (r = 0.79) was found between the 0-year lag of PDO. The NPGO showed significant correlations at all the lags up to 5 years, with strong positive correlation (r > 0.5) after 1–5 years of lag. PDO showed moderate to strong positive correlation (r > 0.3) at 0 lag as well as after 2, 3, 4 and 5 years of lag. On the other hand, NPO showed a weak negative correlation after 1 year of lag while all the other lags displayed stronger positive correlation with moonfish N.CPUE.

The study's findings indicate that catch rates of moonfish have exhibited an increase since 2018, coinciding with the shift to a positive PDO, negative NPGO and negative NPO (Figure 6). Additionally, the catch rates displayed similar fluctuations characterized by cycles lasting 3–4 years (lags of 3–4 years) between 2014 and 2017 for NPGO and PDO.

3.5 | The impact of lags of climatic indices on the N.CPUE of moonfish

The GAMs revealed that the lowest AIC and highest amount of deviance explained was observed when using a 4-year lag of NPGO, followed by a 3-year lag of PDO and, finally, a 4-year lag of NPO (Figure S4 and Table 4). The moonfish N.CPUE was primarily affected

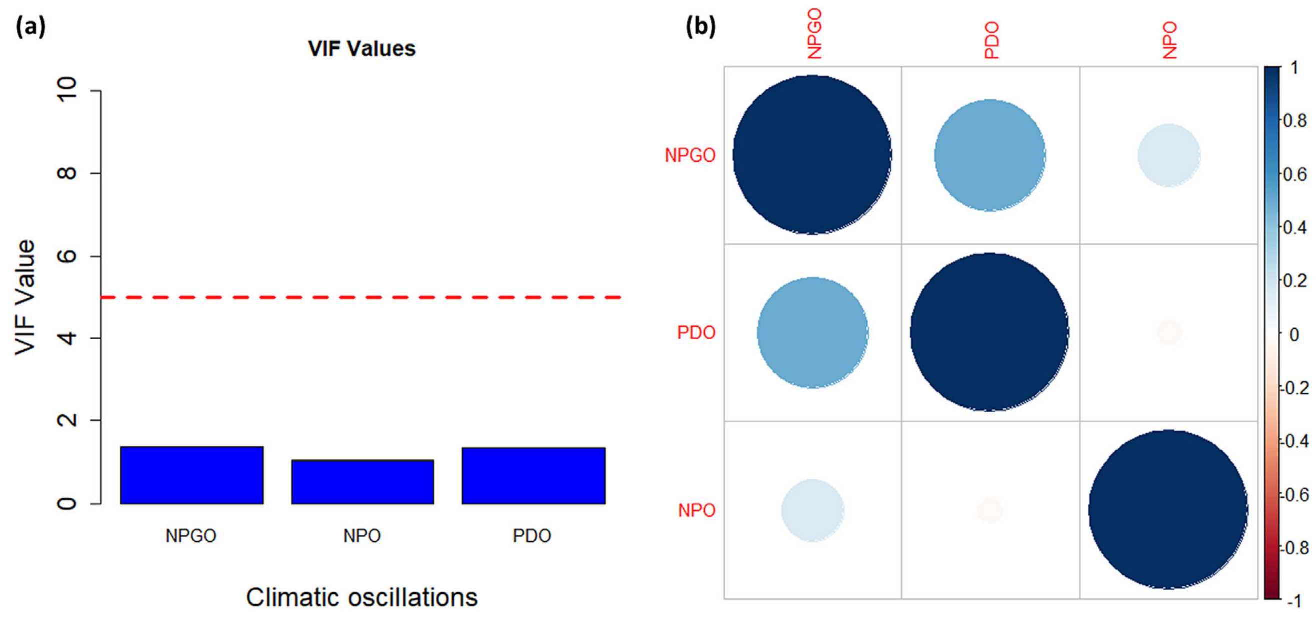

FIGURE 4 Multicollinearity test among climatic oscillations.

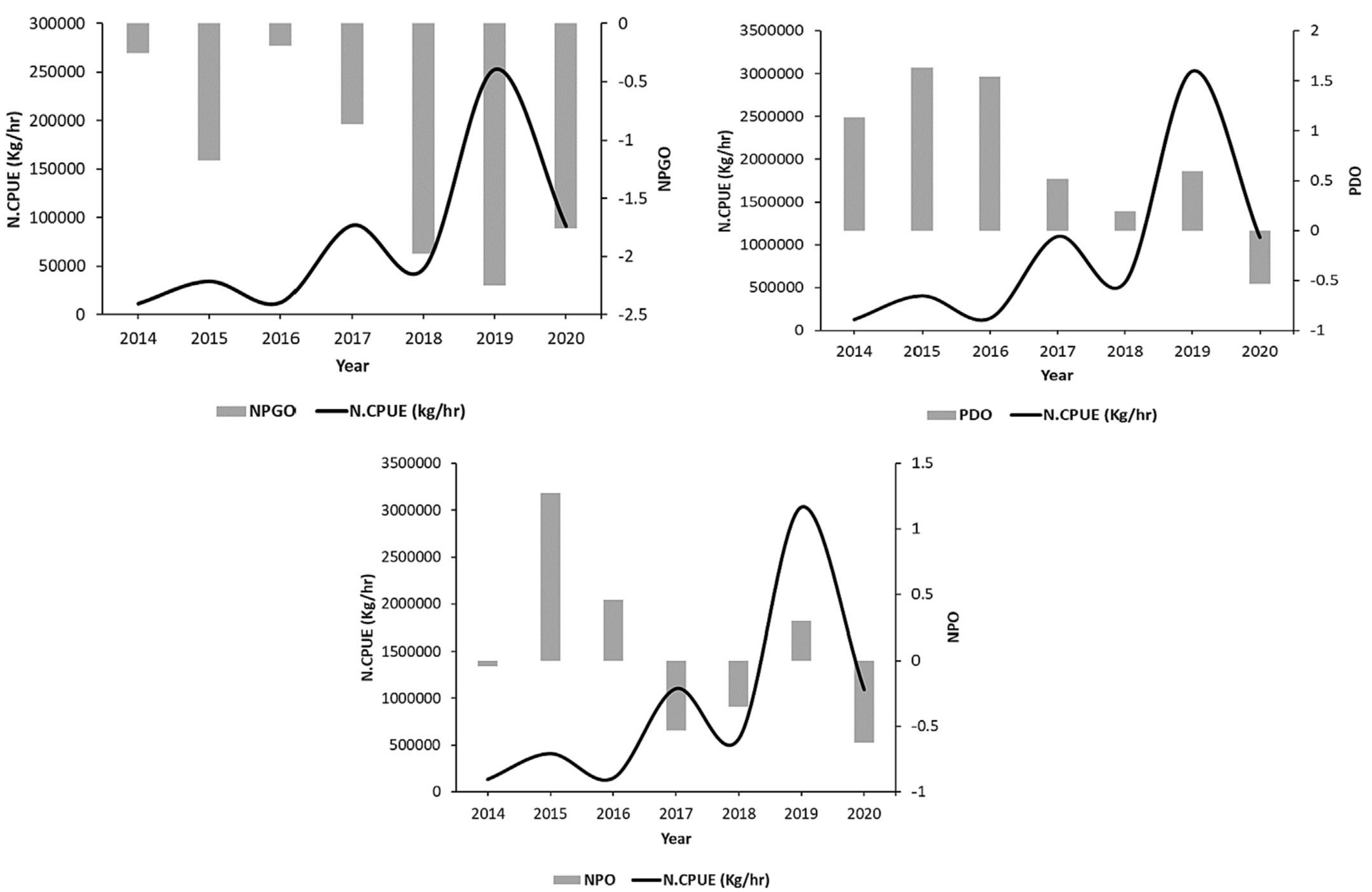

FIGURE 5 The trends in the nominal catch per unit effort (N.CPUE) of moonfish species and the three selected climatic oscillations in the waters surrounding southwestern Taiwan waters (STW) from 2014 to 2020.

by all the lag factors of the three oscillations, particularly including the NPGO with a lag of 4 years, the PDO with a lag of 3 years and the NPO with a lag of 4 years, from the highest to the lowest. These three lag factors accounted for 86.5, 59.6 and 48.5 of the deviance in moonfish catch rates, respectively.

TABLE 3 The comprehensive inventory of Pearson correlation coefficient values (r) of moonfish N.CPUE and the 5-year lags of the selected climatic factors in the waters surrounding STW between 2014 and 2020.

	NPGO	PDO	NPO
Lag		r	
0	−0.7	0.79	**−0.03**
−1	0.63	0.21	−0.17
−2	0.76	0.61	**0.1**
−3	0.66	0.74	0.54
−4	0.64	0.73	0.59
−5	0.59	0.77	0.56

Note: The correlation coefficients with absolute values ≥0.1 are highlighted in bold. Those lag values were not further included in the analysis due to very weak correlation.
Abbreviations: N.CPUE, nominal catch per unit effort; NPGO, North Pacific Gyre Oscillation; NPO, North Pacific Oscillation; PDO, Pacific Decadal Oscillation; STW, southwestern Taiwan waters.

3.6 | WTC

Wavelet analysis identified a significant correlation between N.CPUE and a 4-year lag of NPGO, with periodicities of ∼4 years (Figure 7). This suggests that a 4-year lag of NPGO and moonfish N.CPUE are in anti-phase roughly between 2015 and 2018. A few small but significant blobs of high correlation phases for 4–5 months of NPGO was found between 2016 and 2020 that showed pivotal variations between N.CPUE and NPGO time series. The 3-year lagged PDO revealed two significant in-phase associations with N.CPUE with a periodicity of 9–16 months (∼1.5 years) from 2015 to 2017 and from 2019 to 2020. Lastly, for a 4-year lag of NPO, a large anti-phase association of high correlation was spotted between 2015 and 2018 with a periodicity of <4 months. On the contrary, a significant in-phase relationship was also noticed with a periodicity of 9–16 months between 2016 and 2018.

3.7 | The relationship between climatic oscillations

The climatic indices' correlation analysis exhibited strong linear correlations with absolute values >0.6. Specifically, there is a negative correlation of the 4-year lag of NPGO individually with a 3-year lag of PDO ($r = -0.83$) and a 4-year lag of NPO ($r = -0.78$). A 3-year lag of PDO and a 4-year lag of NPO has a strong positive

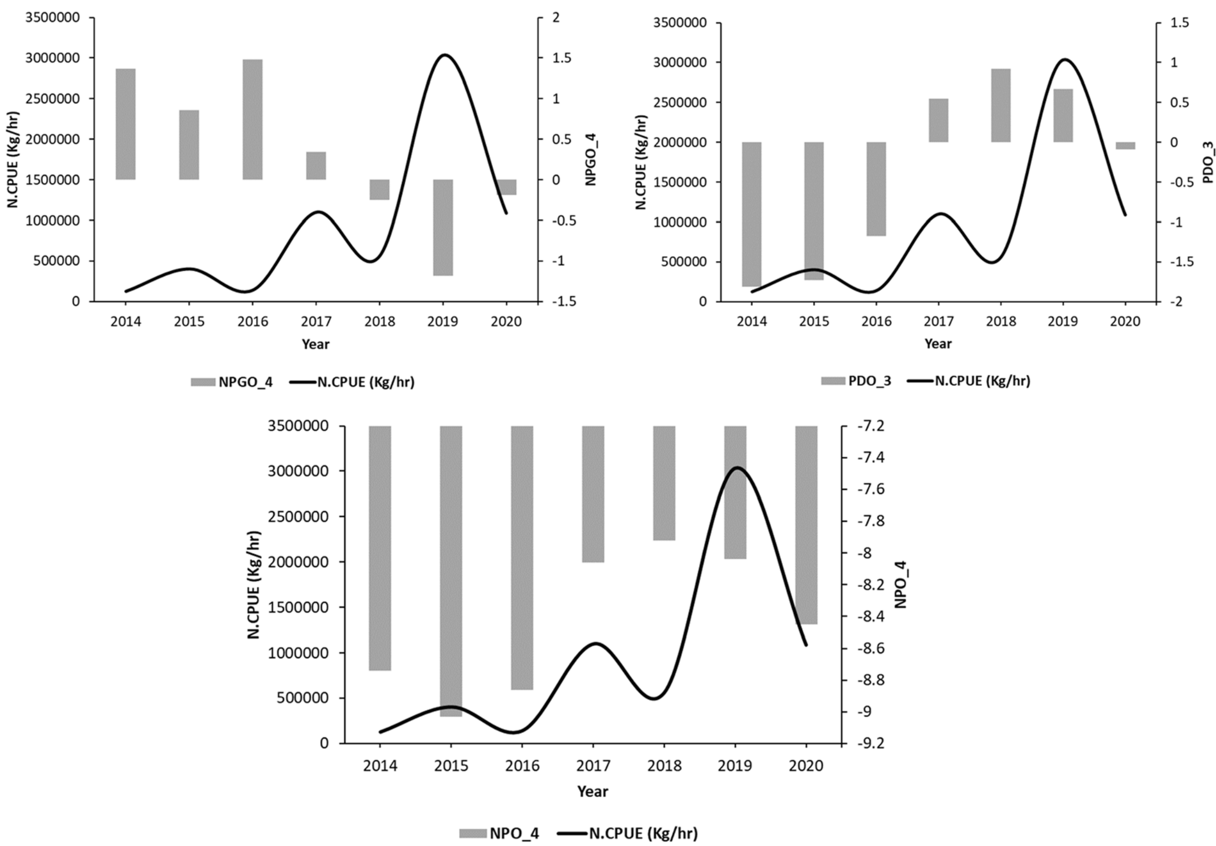

FIGURE 6 The trends in the nominal catch per unit effort (N.CPUE) of moonfish species and the three selected lags of climatic oscillations in the waters surrounding the southwestern Taiwan waters (STW) from 2014 to 2020.

TABLE 4 The relationship between deviance explained (%) and AIC of the climatic oscillations, and the N.CPUE using generalized additive models (GAMs).

Lags	AIC	Deviance explained	Generalized Cross Validation (GCV)	*p*-Value	Significance codes
NPGO_4	12.58224	86.5	0.29387	0.0024**	0.01
NPGO_0	18.39444	69	0.67415	0.0207*	0.05
NPGO_2	21.3696	52.6	1.0312	0.0653***	0.1
NPGO_1	23.58252	34.9	1.4146	0.162	-
NPGO_3	24.50645	25.7	1.6142	0.245	-
NPGO_5	25.07127	19.5	1.7499	0.321	-
PDO_3	20.25146	59.6	0.87897	0.0421*	0.05
PDO_1	21.83953	60.1	1.2543	0.183	-
PDO_4	22.02805	47.9	1.1329	0.085***	0.1
PDO_0	23.06098	36.6	1.313	0.13	-
PDO_5	23.13577	38.9	1.3272	0.134	-
PDO_2	24.24341	39.5	1.687	0.418	-
NPO_4	21.93999	48.5	1.1187	0.082***	0.1
NPO_5	23.81725	32.7	1.4629	0.18	-
NPO_3	23.92701	43.7	1.6385	0.372	-
NPO_1	25.94379	8.79	1.9821	0.518	-

Abbreviations: AIC, Akaike information criterion; N.CPUE, nominal catch per unit effort; NPGO, North Pacific Gyre Oscillation; NPO, North Pacific Oscillation; PDO, Pacific Decadal Oscillation.
***p-Value of 0.1,
**p-Value of 0.01,
*p-Value of 0.05.

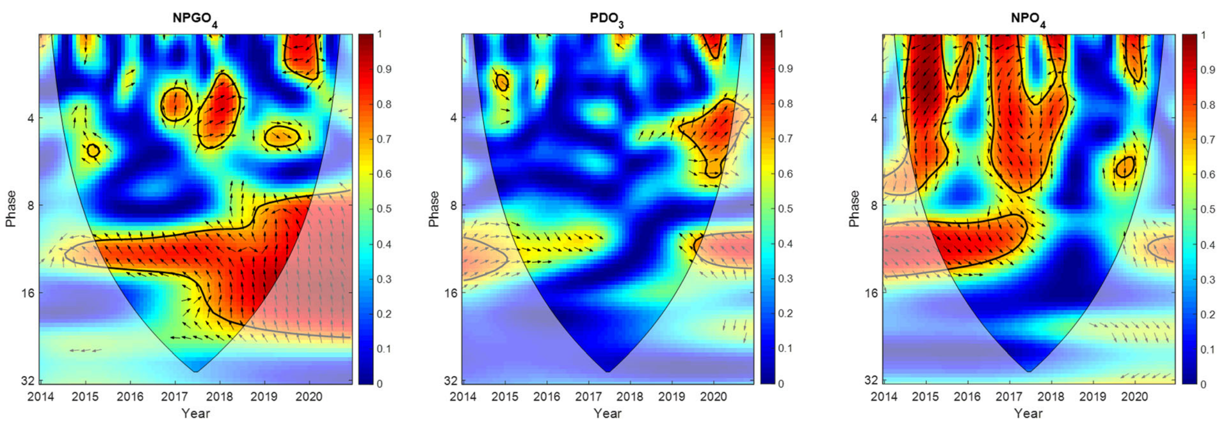

FIGURE 7 The cross-wavelet coherence was calculated between the sum of total nominal catch per unit effort (N.CPUE) and the climatic oscillations. The solid-black contour delineates regions with a confidence level exceeding 95%. The black line indicates the threshold where edge effects become significant. High variability is represented by the colour red, while weak variability is represented by the colour blue. Arrows represent the phase relationship, with in-phase arrows pointing right and out-of-phase arrows pointing left.

correlation of 0.96 that indicates collinearity among these two variable pairs. Additionally, Figure 8 provides visual representation of the expected correlations. Thus, combined modelling of selected climatic oscillations lag pairs were not performed since all of them exhibited high collinearity.

4 | DISCUSSION

The study examines STW moonfish catch data from 2014 to 2020, revealing a link between moonfish purse seine catches and climatic oscillations in the Pacific Ocean, primarily with a 3–4-year periodicity

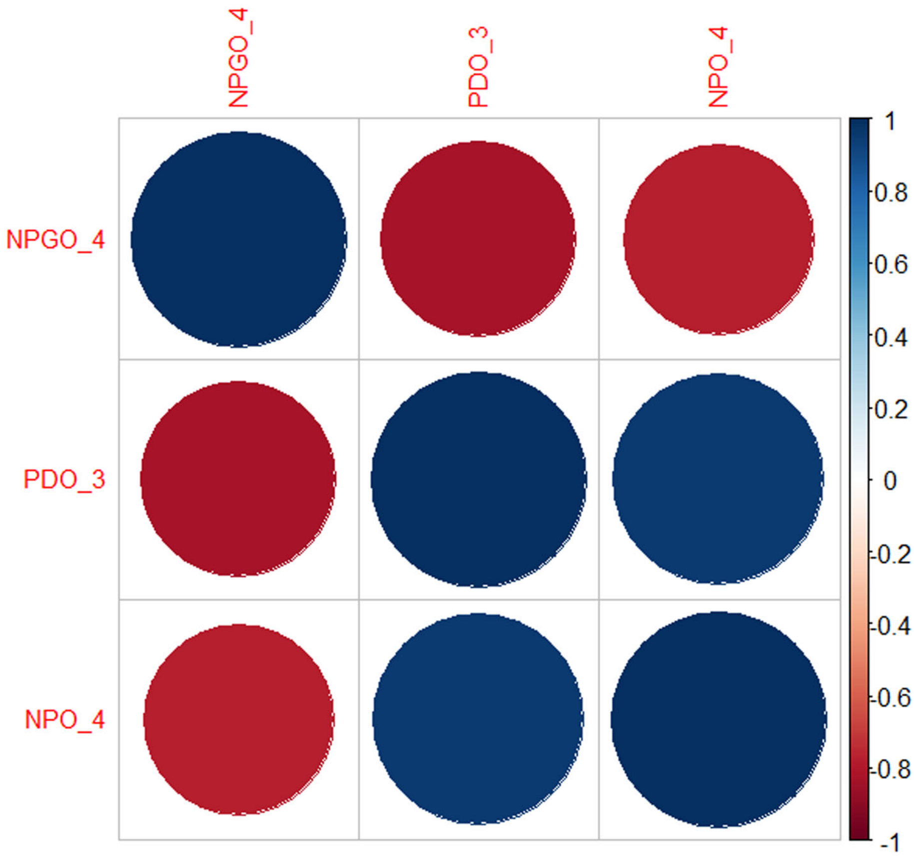

FIGURE 8 A correlation matrix plot to analyse the relationship between variables. It displays the correlation coefficients between each pair of variables in a dataset.

(Tian et al., 2008). In a basic scenario, there is a direct relationship between catch rates and fish abundance. This leads to self-regulating fisheries, as decision-making is influenced by catch rates. If catch rates are proportional to fish abundance, a decrease in catch rates would indicate a decrease in abundance to fishing vessels. As a result, fishing vessels may choose to relocate to other bodies of water where catch rates are anticipated to be higher. This shift in fishing activity, coupled with reduced fishing effort, is expected to allow for the recovery of fish abundance through natural reproduction and a decrease in fishing-related mortality. If catch rates remain consistently high and do not decrease in proportion to the abundance of fish, there is a risk that fishermen may continue to catch fish at unsustainable levels, leading to overexploitation or even the collapse of the fishery (Ward et al., 2013). Moonfish capture in Taiwan has transitioned over the years, with a greater contribution in recent times (Figures 3 and S1). While declining effort may explain the drop in moonfish catch after 2017, the CPUE maintains a consistent upward trajectory, in line with Ho et al.'s (2016) findings that species seasonality impacts catch proportions. Changes in the STW region's SST patterns, influenced by the KC, contribute to variations in moonfish catch, with a notable peak during winter seasons, potentially reflecting shifts in species composition over time (Lu & Lee, 2014). The increased presence of the KC in recent decades, driven by coastal warming, likely plays a role in altering fish catch and structure (Oey et al., 2013). This research examined the relationship between moonfish relative abundance and various climatic variables. The analysis revealed that NPGO, NPO and PDO significantly influenced moonfish catch rate with an ~4-year periodicity from 2014 to 2020. While ONI, SOI, WP, Niño 3.4 and MEI v2 had minimal effects on moonfish, the study established that both negative and positive phases of climate oscillations impacted purse seine moonfish catch rates. This finding aligns with previous research by Ménard et al. (2007) and Lan et al. (2013), indicating that similar catch rate variations may occur in other fisheries targeting different species. Moreover, during positive PDO and negative NPO phases, negative phases are expected to exert a comparable influence on moonfish catch rates. Extreme signals may be amplified by climate oscillations (Vicente-Serrano et al., 2011). The years with the highest CPUE (2017 and 2019) were substantially associated with negative NPO4, positive PDO3 and alternating phases of NPGO4.

Moonfish and PDO displayed their best correlation with no lag, followed by 5, 3 and 4 years. These findings suggest that a negative PDO phase predicts high moonfish levels over a 4–5-year period, while a positive phase leads to lower values. NPGO and NPO indices also exhibit linear correlations with moonfish at the same lag. GAM results emphasize the importance of climatic indices, particularly the NPGO index, in predicting moonfish CPUE over the long term, with the best AIC values indicating its significance in the models. This implies that the NPGO index is a strong predictor of moonfish in the study area. Additionally, PDO, with a 3-year lag, and NPGO and NPO, with a 4-year lag, partially influence moonfish catches. Overall, these GAMs confirm that these indices exhibit a lagged effect on moonfish, with a critical impact expected over a 3 to 5-year period due to future climatic variations. There are also instances of arrows pointing up or down in Figure 7, which means that one variable led another in-phase. This substantially emphasizes that the impact of lag of the oscillations on the moonfish catch rate is observed better after a certain period of time (months or years), rather than having an immediate effect.

Previous studies have shown strong relationships between fish catches and climatic indices that affect ocean productivity and eddy activity, such as NPGO, PDO and NPO. In the high- and mid-latitude Northeast Pacific and Northwest Pacific, respectively, PDO, NPO and NPGO have pivotal ecological effects (Tzeng et al., 2012). Nevertheless, the impact of these climate patterns on the mid-latitude Northwest Pacific remains largely unexplored. This study gives the first empirical investigation of extra-tropical climatic trends and annual moonfish catchability. Miller et al. (2009) found that extra-tropical climatic trends alter ocean productivity and eddy activity, influencing Japanese eel recruitment. We accept that the correlative analysis may have certain limitations that facilitates the need for further ocean dynamics research, including using satellite and ocean modelling tools.

Moonfish catchability is affected by SST and thermocline changes caused by climate variability, and this effect may be responsible for variations in catch rates observed in this study (IATTC, 2017). Positive PDO phases result in lower SSTs, an increased MLD and a weakened KC in the central and western North Pacific, with warmer SSTs in the eastern North Pacific (Yatsu et al., 2013). In the northern Pacific, weaker Kuroshio effects improve fish catches (Chavez et al., 2003). The KC and NCCC geostrophic transports explain the moonfish capture rate-PDO association. While the westerlies across the western North Pacific strengthen, the Aleutian low-pressure core deepens and advances southward during the positive PDO period. Mid-latitude SSTs decrease because of increasing southerly Ekman movement. The positive PDO weakens Kuroshio transport as the zero wind stress curl moves south (Zhang et al., 2012). In winter, greater northeasterly winds help the cold NCCC penetrate the TS and slow down the northward movement of the warm KC. Thus, moonfish distribution may have extended towards the southern TS owing to enhanced southbound NCCC under positive PDO, thereby increasing the CPUE (Figures 5 and 6). Thus, surface fishing in this location has made this species more vulnerable. Our analysis suggests improving detection in future studies. Studies have shown that oscillations like NAO may affect albacore tuna reproduction and spawning frequency across their lifetime. Considering the findings, the observed delay between the PDO and moonfish CPUE may be due to a cumulative influence on moonfish physical state and spawning intensity. Although the health and spawning intensity of moonfish in relation to Pacific Ocean climate cycles remain understudied, this study highlights a potential multi-year lag effect on recruitment and/or a cumulative impact on moonfish condition and spawning intensity. The specific mechanism is not yet known, and it remains uncertain whether one hypothesis is more accurate than others or if a combination of factors is involved.

The effect of NPGO-associated Rossby waves from the central North Pacific is delayed by years and alter Kuroshio physical state and zooplankton abundance (Di Lorenzo et al., 2013). For example, negative NPGO slows KC and enhances zooplankton, and vice versa. So, the negative NPGO anomaly helps moonfish migrate and feed in KC. Adoption of the NPGO with a time lag of 4 years coincides with the highest moonfish catch rate of 2019 corresponding with a negative phase. After 2016, PDO became positive while NPGO became negative. Mantua and Hare (2002) found that positive NPGO events and negative PDO events cool Pacific Ocean SST. The cooler SST increased Pacific Ocean coastal primary production, which may aid moonfish larvae (Kilduff et al., 2015). PDOs and NPGOs may also affect small invertebrate and coastal fish recruitment and abundance over 2–4 years (Zwolinski & Demer, 2014). These findings indicate that climatic oscillations may have influenced Taiwanese purse seine fisheries not only in Taiwan but also in nearby regions, aligning with global fisheries trends. Climate change and rising sea levels are expected to have the greatest impact in low-lying coastal areas and large ocean basins (Barman et al., 2023; Barman & Bora, 2021). According to climate change scenarios based on the IPCC A2 model, it is projected that the 20°C isotherm in the TS will move northward to 25.5°N by 2050 and further to 26°N by 2075. Fluctuations in catch levels, climate indices and costs have prompted the adoption of purse-seiner and gillnet vessels (Lan et al., 2014). Changing global conditions impact fishing catch and distribution patterns, with the PDO and NPGO shown to affect Chl-a concentration, nutrient levels and fish stock captures in the North Pacific (Yati et al., 2020). The delayed upwelling and its association with NPGO can have significant effects on nutrient availability and productivity at lower trophic levels, impacting the coastal and offshore ecosystem. Upwelling events in STW lead to increased moonfish capture and higher biological output (Chenillat et al., 2012). Furthermore, the timing of upwelling, whether early (NPGO+) or late (NPGO−), significantly influences ecosystem productivity throughout the year.

A strong atmospheric circulation pattern, the NPO, is thought to affect central North Pacific sea surface temperature anomalies (SSTA) (Vimont et al., 2009). The middle and eastern tropical Pacific may have NPO-induced wind stress anomalies and subsurface temperature and heat content anomalies. These anomalies may impact SSTA in the central and eastern equatorial Pacific all year (Anderson, 2007). The NPO SLP variability may link Pacific inter-annual and decadal climatic variability like the PDO, explaining the strong NPO-PDO collinearity found in the present study. The PDO and NPGO have increased variability in recent decades (Di Lorenzo et al., 2008). CPW, NPO and NPGO may drive Pacific atmospheric, oceanic and biological system changes that might influence moonfish catch from 2014 to 2020 and even in the future. The relationship offers a new perspective on the ocean–atmosphere interactions in the Pacific decadal climate research.

This analysis suggests that purse seine fleet dynamics, atmospheric oscillations and other unknown physical and biological systems in the STW region of the Pacific Ocean may influence the supply of moonfish. This can occur through various mechanisms, including a decrease in CPUE and fishing effort due to unfavourable weather conditions. Conversely, these oscillations may also lead to an increase in the seasonal abundance of specific species and impact population survival (Barange et al., 2018). Small coastal fishes like

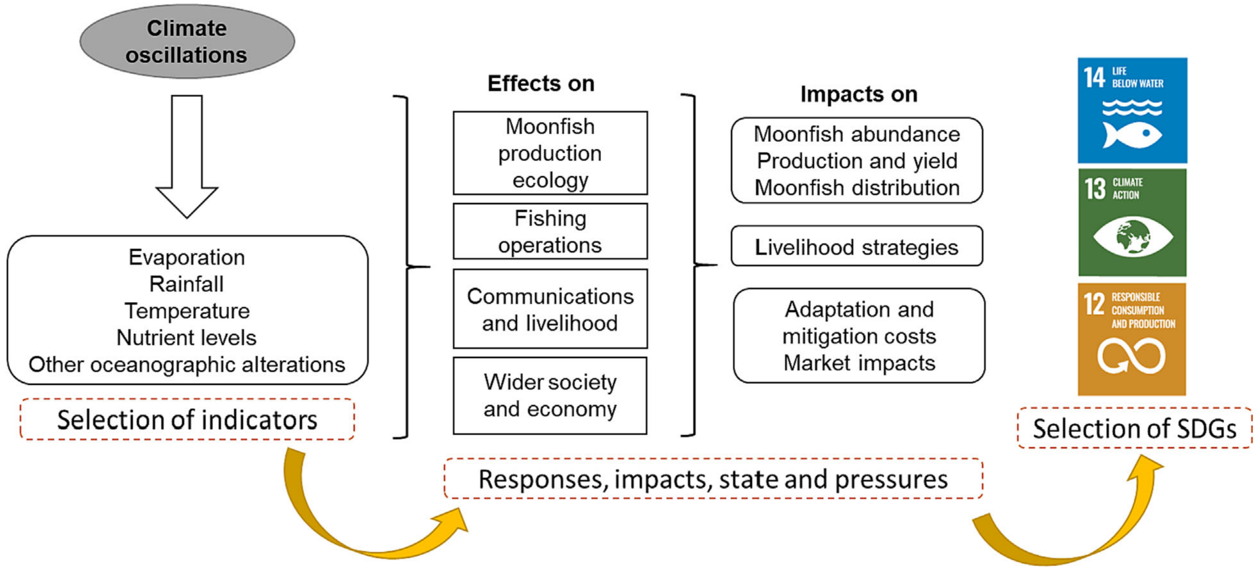

FIGURE 9 A thematic approach of how this study would focus on multiple aspects including climate crisis, moonfish resource productivity and sustainable commercial production by identifying climatic oscillations as relevant indicators to assess moonfish resource usage.

M. maculata exhibit high sensitivity to environmental forcing and display significant variability in their abundance (Alheit et al., 2012). The abundance of round sardinella (*Sardinella aurita*) has been observed to increase and expand northward along the western Mediterranean coasts. This trend is believed to be linked to rising sea water temperatures. Previous studies by Sabatés et al. (2013) have documented this phenomenon. The annual differences in moonfish catch rates between 2014 and 2020 can be attributed to their numerical abundance and the influence of different temperature windows resulting from various climatic indices. Mellado-Cano et al. (2019) showed that the various phases of the East Atlantic pattern can influence extreme high temperature events associated with the NAO and can even cause a reversal of climate variability patterns. The relationship between fluctuations in landings and market prices of representative species in the region, as well as atmospheric indices, can verify this. Further research on fishing gear configurations and targeting behaviour might help explain moonfish CPUE as well as their spatial distribution in the studied area. Small coastal, pelagic and demersal species respond differently to climatic fluctuations. Small coastal species react individually, whereas demersal species respond collectively. To preserve the ocean resources, small coastal fisheries like moonfish should be managed under the lens of sustainable development goals (SDGs; Figure 9). The findings of this study have implications for understanding the delayed impact of climatic oscillations on the moonfish resource in Taiwan. Additionally, these results can inform the development of management recommendations aligned with SDGs 2, 8, 13 and 14 (Ntona & Morgera, 2018). To achieve sustainable development in fisheries, it is necessary to collect fishery data regularly, classify moonfish based on their length ranges and develop habitat models that encompass the different stages of the life cycle of the species (Shao et al., 2011). Our present study along with previous research shows that small forage fish species are especially sensitive to increasing water temperatures and heavy fishing. This increased vulnerability may cause population decreases or collapse, resulting in catch rate changes over time (Tian et al., 2008). To guarantee sustainable exploitation of such fish species and allied fisheries, additional care is needed considering the expected severe climatic conditions in the future. Fisheries management must address responses of marine organisms and resources to climate change. Given the significance of the SSF sector in Taiwan's economy, our findings highlight the need to prioritize the enhancement of adaptive capacity and the integration of climate change considerations into both national and regional policies.

5 | CONCLUSIONS AND REMARKS

- This study examined the influence of climatic fluctuations on moonfish catch rates in the waters off the southwestern Taiwan, demonstrating an inverse relationship between NPGO, NPO, PDO and CPUE values, with recurring patterns every 3–4 years.
- The peak fishing season for moonfish occurred from January to March, with the fishing grounds located near the coast.
- Our findings provide initial insights into the impact of climatic variability on western Pacific Ocean moonfish catch rates, although the underlying processes remain uncertain.
- In the context of moonfish landings, our analysis revealed that the NPGO variable lagged by 4 years, PDO variable lagged by 3 years and NPO variable lagged by 4 years exhibited the strongest positive influence with the response variable N.CPUE (86.5%, 59.6% and 48.5% deviance explained).
- Furthermore, it appears that higher negative values of the NPGO and higher positive values of both PDO and NPO have a negative impact on the moonfish landings of the same year (Figure 5).

- The majority of fishing data was collected from Taiwanese purse seine vessels operating in the Pacific Ocean during the period from 2014 to 2020, ranging to about 98% (Figure S2).

6 | LIMITATIONS OF THIS STUDY

To comprehend productivity trends in this region and their linkages to other areas, further research is needed. Additionally, the consequences of lagged oscillatory processes on moonfish populations and catches, along with the role of fishing behaviour, necessitate investigation. Fine-scale fishing data covering 7 years and incorporating up to 5-year oscillation lags pose constraints on further research and measurement of their connections. Ensuring the quality of catch data and addressing discrepancies in climate oscillation lags are crucial. Longer time series with more comprehensive information on catch, effort and CPUE are essential for a deeper understanding of the strength of associations among different climatic indices.

AUTHOR CONTRIBUTIONS

Concept and design: Aratrika Ray, Sandipan Mondal and Ming-An Lee. *Data acquisition*: Ming-An Lee. *Analysis and data interpretation*: Aratrika Ray, Sandipan Mondal and Riah Irawati Sihombing. *Article drafting*: Aratrika Ray. *Critical supervision and revision*: Kennedy Edeye Osuka and Ming-An Lee.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing interests.

DATA AVAILABILITY STATEMENT

For access to the data used in this study, please contact the following email address: malee@mail.ntou.edu.tw.

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