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RESEARCH PAPER

Environmental Drivers of Fishing Success: A Multiyear Analysis of Purse Seine CPUE in the Aegean Sea

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Abstract

Fisheries are highly vulnerable to environmental and anthropogenic pressures and evaluating fish stocks is crucial for sustainable management. This study aims to assess the effects of sea surface temperature (SST), sea surface salinity (SSS), sea surface chlorophyll-a concentration (SSC), and lunar phases on the catch per unit effort (CPUE) of purse seine fisheries in the Aegean Sea. Catch data were collected from a purse seine vessel operating in İzmir Bay between 2017 and 2023. A generalized linear model (GLM) was employed to standardize CPUE values, considering various temporal and environmental factors. Results indicated significant variability in CPUE across years, months, and moon phases, with the highest CPUE observed during January and the last quarter lunar phase, while April and the full moon phase exhibited lower catch rates. SSC had a significant negative effect on CPUE, whereas SST and SSS showed no statistically significant influence. The decline in CPUE over the study period suggests increasing pressure on fish stocks, highlighting the importance of monitoring environmental changes for effective fisheries management. This study contributes to filling the knowledge gap on the impacts of SST and SSC on purse seine fishing in the Aegean Sea, offering insights for future fisheries policies and conservation efforts.

Introduction

Fisheries are highly sensitive, not only to anthropogenic pressures but also to environmental variables. Abiotic factors such as temperature, salinity, light, oxygen, currents, wind, and precipitations affect the dynamics of the food chain, ultimately, the density and accessibility of fish populations are also affected (Miller & Schneider, 2000; Avsar, 2016). Environmental factors can also change depending on climate change, and these factors influence the survival capabilities of organisms at the ecosystem level (Brander, 2007; Gamito et al., 2015; Tosunoglu & Ceyhan, 2021), therefore the past and future distribution of biodiversity are determined. Additionally, these changes disrupt marine biodiversity and ecosystems, posing a major risk to global fishery stocks (Cheung et al., 2009; Medellín – Ortiz et al., 2022).

Accurately evaluating existing stocks, is essential for sustainable fisheries management (Hilborn & Walters, 2013). Due to the financial challenges of collecting fishing-independent data, many stock evaluations rely on fisheries-dependent data. The most common source of this data is catch and effort information, typically obtained from commercial or recreational fisheries. This information reveals the Catch Per Unit Effort (CPUE) (Maunder & Punt, 2004).

Changes in fish abundance in the ocean are important information for fisheries management. CPUE data allows us to see the performance of the fishing gear and make determinations about resource availability, as it allows us to see changes in catch amounts (Abdellaoui et al., 2017). However, although the most common dataset used in stock management in fisheries is CPUE, its direct use can be misleading due to spatial, temporal, and environmental factors and fishing capacity changes (Hua et al., 2019). For this reason, Maunder and Punt (2004) reported that standardization of CPUE to eliminate the changing effects on CPUE is one of the most widely applied methods for fisheries analyses. The standardized CPUE data is used to generate information about the impact of fishing on stocks, as well as to see the effects of environmental changes and to compare fishing activities across different regions.

In order to obtain catch and effort data, it is necessary to be in contact with the fishing fleets in the targeted area. Furthermore, for sustainable fishing approaches, it is important to understand the fishing fleets and their fishing capacities. In the Mediterranean and Black Sea, small-scale fishing vessels represent 82% of the fleet, while purse seine and trawl vessels cover only 13% (purse seiners 5%). Despite this, purse seine vessels have been the fleet group responsible for more than half of the total catch (FAO, 2023). Likewise, purse seine vessels, which are also an important part of Turkish marine fisheries, represent only 2.80% (392 vessels) of the entire fishing fleet in Türkiye. However, it produces nearly half of the total marine catch production (TurkStat, 2023).

Pelagic fish, which constitute the majority of the catch composition in purse seine fisheries, are highly sensitive to climatic and environmental changes due to their population characteristics (Blaxter & Hunter, 1982; Cole & McGlade, 1998). This sensitivity makes purse seine fishing particularly vulnerable to environmental fluctuations, and understanding how these factors impact CPUE is crucial for effective fisheries management (Tosunoglu et al., 2021).

Building on this, Tosunoglu et al. (2021) used generalized additive models (GAM) to investigate the relationships between CPUE and factors such as sea surface temperature (SST), lunar phases, fishing area, and the use of light in purse seine fisheries in İzmir Bay. Similarly, Ceyhan and Tosunoglu (2022) applied GAM techniques to examine the effects of environmental variables on bycatch from purse seine vessels. While previous research has focused on standardizing CPUE data and examining its relationship with various environmental factors (Teixeira et al., 2016; Abdellaoui et al., 2017; Ceyhan et al., 2018; Runcie et al., 2018; Karakulak & Ceyhan, 2024), studies specifically addressing purse seine fishing in the Aegean Sea remain limited. Furthermore, a critical knowledge gap exists regarding the influence of SST and sea surface chlorophyll-a concentration (SSC) on purse seine fisheries in this region.

This study aims to fill these gaps by investigating the relationships between standardized CPUE and key environmental factors—including SST, sea surface salinity (SSS), SSC, and lunar phases—within the purse seine fisheries of the Aegean Sea. Using daily catch data from 2017 to 2023 and applying generalized linear models (GLMs), this research seeks to determine how these oceanographic and temporal variables influence CPUE, while also identifying trends in fishing productivity. The findings will contribute to a deeper understanding of the environmental drivers affecting purse seine fisheries and provide valuable insights for future management and conservation efforts in the Aegean Sea.

Materials and Methods

CPUE data, measured in kilograms for the target species (*Sardina pilchardus* and *Engraulis encrasicolus*), were collected daily from 2017 to 2023 from a purse seine vessel operating in İzmir Bay. Data were gathered through interviews with the vessel's captain during the fishing season, which runs from September 1 to April 15. The dataset used in the analyses includes date (day, month, year), lunar phases, season, SST, SSC, SSS, species caught and catch information in kilograms. Environmental variables, including SST, SSC, and SSS were obtained from the E.U. Copernicus Marine Service database (2023a, 2023b) as daily values and incorporated into the analysis to examine their effects on catch rates. Lunar phases during fishing operations were classified into four categories—new moon, first quarter, full moon, and last quarter—based on the lunar calendar. Bycatch (both retained and discarded species) was excluded from this analysis.

The CPUE was calculated from three parameters as below for each fishing vessel:

$$F = H \times D$$

$$CPUE = B \times F^{-1}$$

Where F represents the fishing effort, H is the number of hauling, D is the fishing day, and B is the biomass of landings.

The normality of the data distribution was evaluated by Kolmogorov-Smirnov test and Shapiro-Wilk test. It was seen that the data did not follow a normal distribution, so normalization statistics were applied. For the normalization of the dataset, 7 different normalization methods; arcsinh transformation, centering and scaling, double reciprocal log transformation, logarithmic transformation, rank normalization transformation, square root transformation, and Yeo-Johnson transformation were tested using the generalized cross-validation process. As a result, the Yeo-Johnson transformation was the most appropriate method, and the normalized CPUE values were subsequently used for modeling.

Before model selection, multicollinearity among the predictor variables was assessed using a Variance Inflation Factor (VIF) analysis, which quantifies how much variance in each regression coefficient is inflated due to collinearity with other predictors. VIF values above 5 or 10 indicate high multicollinearity, and this step ensures the stability of the regression model.

Additionally, a Pearson correlation matrix was computed to assess relationships between temporal and environmental variables, including year, month, season, moon phases, SST, SSS, and SSC. Hierarchical clustering was applied to the correlation matrix to enhance the interpretability of these relationships. This comprehensive approach provided insights into potential collinear relationships and facilitated the identification of key patterns between oceanographic parameters and temporal factors.

In order to find the regression analysis method that best explains the relationship between the dependent and independent variables, 7 models were created using generalized linear model (GLM) techniques. The Akaike Information Criterion (AIC) (Akaike, 1974) was used to select the best model. To assess the effects of independent variables on CPUE, the model with the lowest AIC value was identified as the generalized linear modeling (GLM) technique with Gaussian distribution (Nelder & Wedderburn, 1972), and this model was employed.

All analyses were performed using R version 4.3.3 (R Development Core Team, 2024). The following R packages were used: mgcv for model fitting (Hastie & Tibshirani, 1986), tidyverse (Wickham et al., 2019), car (Fox & Wisberg, 2019), bestNormalize (Peterson & Cavanaugh, 2020; Peterson, 2021), and corrplot (Wei & Simko, 2024).

Results

Catch per unit effort (CPUE) for the purse seine vessel varied significantly across years, months, and moon phases, highlighting clear temporal patterns. In terms of yearly trends, 2017 had the highest mean CPUE at 6442 kg (haul day) $^{-1}$, with a maximum value of 24500 kg (haul day) $^{-1}$, and a median of 4536 kg (haul day) $^{-1}$ (Figure 1). In contrast, 2019 recorded the lowest mean CPUE at 3069 kg (haul day) $^{-1}$, with a maximum of 9772 kg (haul day) $^{-1}$ and a median of 2548 kg (haul day) $^{-1}$. A slight recovery was observed in 2022, where the mean CPUE was 4127 kg (haul day) $^{-1}$, before declining again in 2023, with a mean of 3444 kg (haul day) $^{-1}$ and a median of 2744 kg (haul day) $^{-1}$. Across all years, the interquartile range (IQR) was widest in 2017 (1852–10202 kg (haul day) $^{-1}$), indicating substantial variability in catch rates during this year.

Monthly trends also revealed distinct seasonal patterns. January had the highest mean CPUE at 5734 kg (haul day) $^{-1}$, with a maximum catch of 17878 kg (haul day) $^{-1}$ and a median of 4637 kg (haul day) $^{-1}$, indicating strong fishing activity early in the year (Figure 2). In contrast, April exhibited the lowest mean CPUE at 2639 kg (haul day) $^{-1}$, with a minimum of 448 kg (haul day) $^{-1}$ and a median of 2200 kg (haul day) $^{-1}$, reflecting reduced fishing effort at the season's end. September and October were also high-performing months, with mean CPUEs of 5222 kg (haul day) $^{-1}$ and 5369 kg (haul day) $^{-1}$, respectively, and a maximum catch of 24500 kg (haul day) $^{-1}$ in October.

CPUE also showed variability across moon phases. The highest mean CPUE was recorded during the last quarter at 5364 kg (haul day) $^{-1}$, with a maximum of 24500 kg (haul day) $^{-1}$ and a median of 4130 kg (haul day)

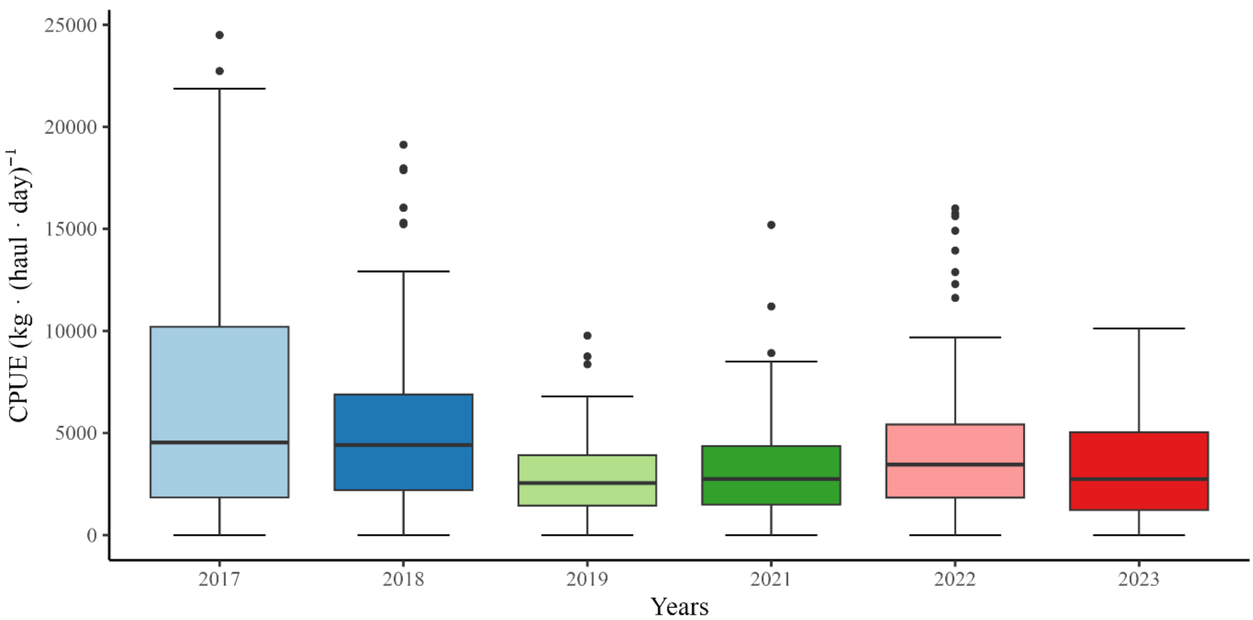

Figure 1. The CPUE values of a purse seine vessel in the Aegean Sea by years.

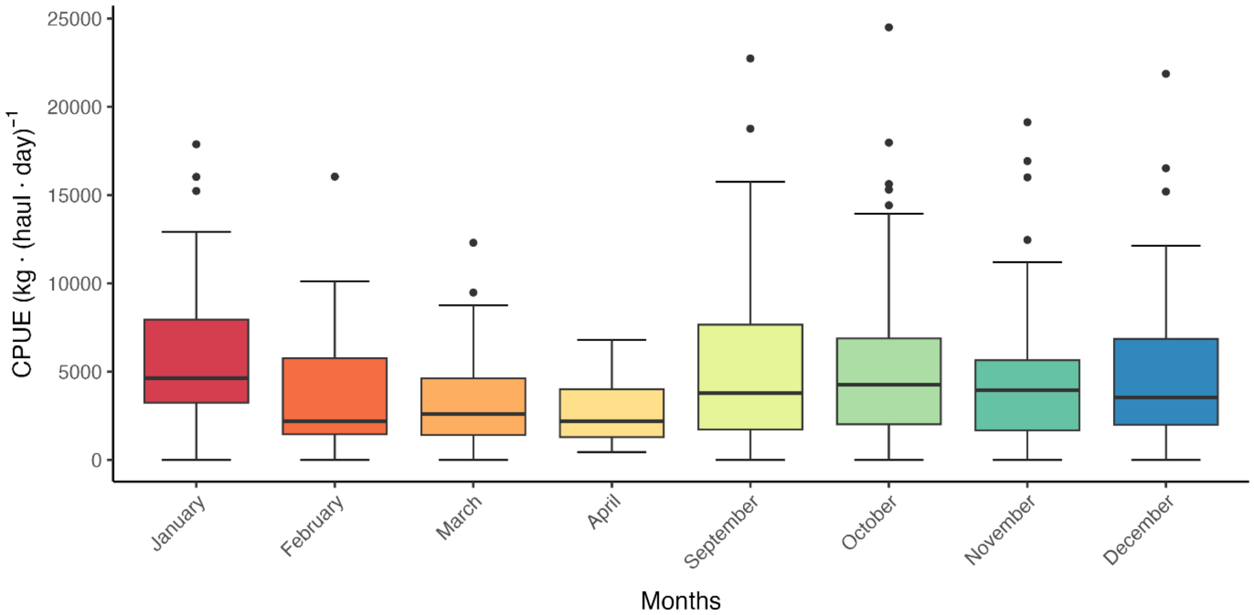

Figure 2. The CPUE values of a purse seine vessel in the Aegean Sea by months.

$^{-1}$ (Figure 3). Conversely, the full moon phase had the lowest mean CPUE of 3869 kg (haul day) $^{-1}$, with a median of 3180 kg (haul day) $^{-1}$. The last quarter phase exhibited the widest variability, with an IQR from 2009 to 7322 kg (haul day) $^{-1}$, while the full moon phase displayed a narrower range from 1361 to 4970 kg (haul day) $^{-1}$.

Overall, these results show that CPUE was highest in January, October, and during the last quarter moon phase, while April and the full moon phase exhibited lower catch rates. These patterns highlight the influence of both temporal factors and lunar phases on fishing productivity, as demonstrated by the box plot graphs for each variable.

The correlation matrix provided insights into the relationships between the key variables—year, month, season, moon phases, SST, SSS, and SSC. Daily values of these environmental parameters were used in the analysis. A moderately positive correlation between year and SSC (r=0.38) suggests that chlorophyll-a levels have increased over time. On the other hand, year exhibited weak negative correlations with SST (r=−0.23) and SSS (r=−0.24), indicating slight decreases in these sea surface conditions over time. Season demonstrated a strong positive correlation with SST (r=0.76) and a moderate correlation with SSS (r=0.50), highlighting seasonal variations in temperature and salinity. The strong negative correlation between SST and SSC (r=−0.67) suggests that higher sea surface temperatures are associated with lower chlorophyll-a concentrations, which may reflect biological processes influencing phytoplankton growth. Moon phases exhibited little to no correlation with the other variables, with the highest being a weak positive correlation with SSC (r=0.008). The expected correlation between month and season was strong (r=0.69), given their temporal overlap. Overall, the correlation matrix underscores the significant effects of seasonality and temperature on chlorophyll-a levels and salinity, while temporal and lunar factors appear to have weaker associations with these oceanographic parameters (Figure 4).

Results in Table 1 showed that all predictors had VIF values well below the critical threshold of 5, indicating that multicollinearity is not a significant concern in this dataset. The predictor season had the highest VIF (4.40), corresponding to a $GVIF^{1/(2Df)}$ value of 1.45, suggesting moderate multicollinearity but still within acceptable limits. SST also exhibited moderate VIF (3.57, $GVIF^{1/(2Df)}$=1.89). All other predictors, including year, month, salinity, chlorophyll-a concentration, and moon phases, had VIF values ranging from 1.04 to 2.30, indicating low levels of multicollinearity (Table 1). Overall, the VIF analysis suggests that multicollinearity is not a major issue in the model, and the predictors can be retained without concerns of inflated variances or unstable coefficients.

To determine the best predictors of CPUE, a series of generalized linear models (GLMs) were developed. Seven models were constructed, incorporating both temporal and oceanographic variables such as year, month, season, SST, SSS, SSC, and moon phases. The selection of the best model was based on the Akaike Information Criterion (AIC), where lower AIC values indicate a better fit. Model 1, which included only year as a predictor, resulted in an AIC of 1585 (Table 2). As additional variables were introduced in subsequent models, the AIC values varied, with Model 7, which included all predictors, yielding the lowest AIC (1571). This suggests that Model 7, which accounts for both temporal and environmental factors, provides the best fit for explaining the variability in CPUE. Consequently, Model 7 was selected as the optimal model, reflecting

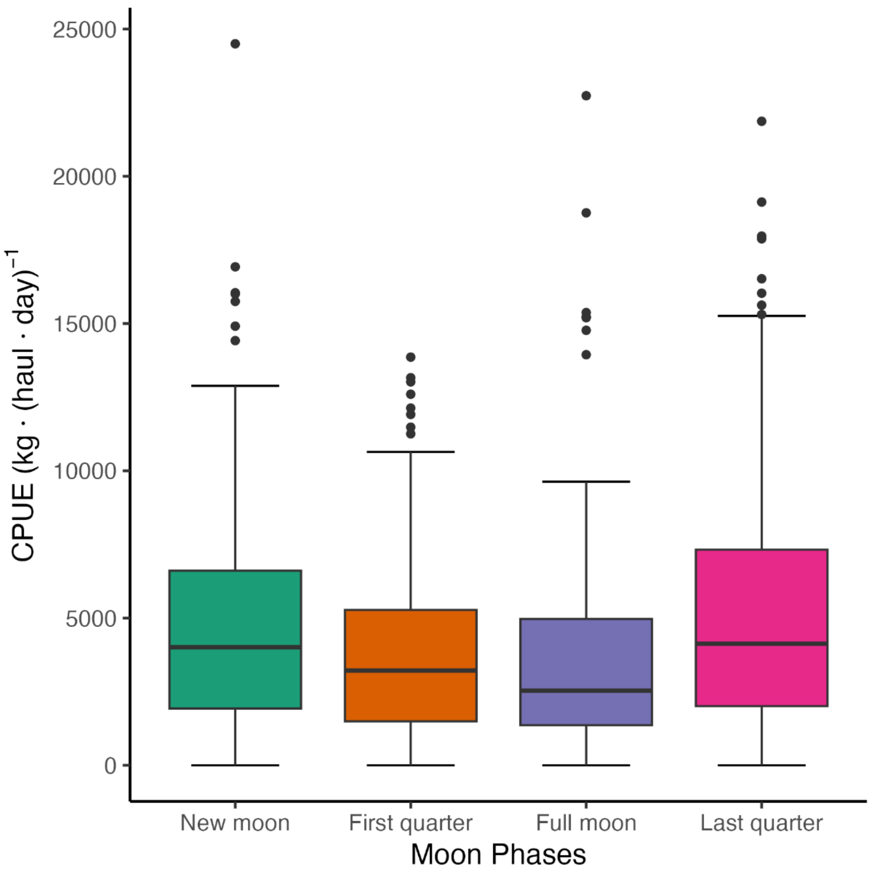

Figure 3. The CPUE values of a purse seine vessel in the Aegean Sea by lunar phases.

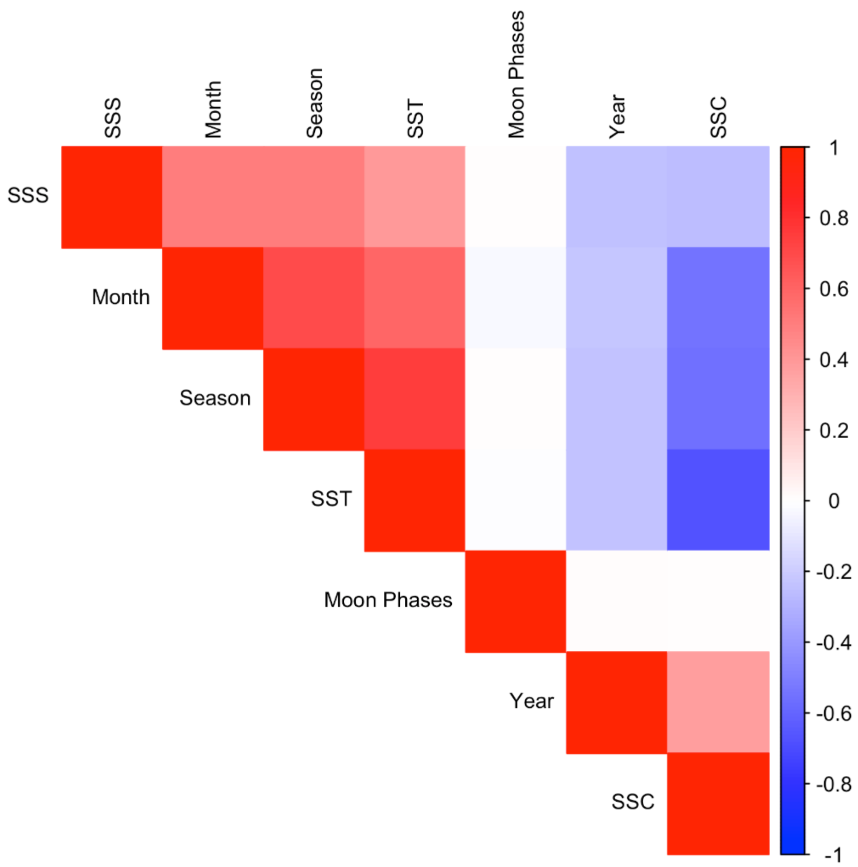

Figure 4. Correlation plot illustrating the relationships among variables included in the analysis.

the importance of integrating a comprehensive set of predictors to understand CPUE dynamics.

The diagnostic plots for Model 7 indicated that the residuals were well-behaved. The deviance residuals formed a straight line in the QQ plot (Figure 5a), suggesting that the normalized CPUE values followed a normal distribution. Furthermore, the residuals appeared independent and well-distributed (Figure 5b), confirming the validity of the model assumptions

The analysis revealed that the year had a significant negative effect on CPUE, indicating a slight decline in CPUE over time. SSC was also found to be an important predictor, suggesting that higher chlorophyll-a concentrations were associated with lower CPUE values, potentially reflecting changes in productivity or resource availability. Additionally, the full moon phase had a significant negative effect on CPUE, indicating reduced catch rates during this lunar phase (Table 3).

Other variables, including month, SST, SSS, winter, and spring, did not exhibit significant effects on CPUE at the 5% significance level. However, spring was close to the borderline of significance (P=0.0537), suggesting a possible seasonal trend in CPUE reduction during this period.

These results suggest that year, SSC, and lunar phases, particularly the full moon, are key factors influencing CPUE, while other environmental and temporal factors show less consistent effects on CPUE.

Discussion

In the presence of a linear relationship between dependent and independent variables, the use of GLM techniques for standardization of fisheries-dependent data (commercial catch data, effort data, surveys, etc.) is quite common (Venables & Dichmont, 2004). However, due to the lack of a linear relationship between environmental factors and catch data in fisheries, there are also studies using GAM techniques (Walsh & Kleiber, 2001; Hua et al., 2019). Li et al. (2023) used GLM and GAM techniques to explore the relationship between environmental changes and CPUE. Although GLM results were highly significant, GAM was reported to be the better model based on the AIC value. In this study, the GLM technique produced the best results in terms of AIC value.

In the Eastern Mediterranean, Karakulak and Ceyhan (2024) used GAM techniques to determine the effects of variables (SST, salinity, fishing vessel measurements, temporal-spatial parameters) on Atlantic bluefin tuna (*Thunnus thynnus*) CPUE, reporting that the lowest CPUE occurred in July and the highest in June. In addition, a statistically significant negative effect of year on CPUE was found (P<0.05). In the Western Mediterranean, Jghab et al. (2019) also examined the effects of environmental and temporal variables such as SST, SSS, and SSC on the catch of *S. pilchardus*. They found that winter (February-April) had the lowest sardine catches, with increasing amounts from spring to autumn, along with a significant decline in annual sardine catches. In our study, we observed a negative correlation between year and CPUE, with CPUE decreasing by almost half from 2017 to 2023. It is also notable that CPUE decreased during February-April, before the fishing season closure in Turkey (April 15), and increased in September-October after the season reopening. This may reflect the beneficial effects of fishing bans on fish abundance.

Many studies have examined the effects of lunar phases on fish abundance. In Hawaii, Bigelow et al. (1999) used GAM to investigate the effects of various factors, including lunar phases and SST, on the CPUE of *Xiphias gladius* and *Prionace glauca*, and found that the lunar index was significantly effective for the CPUE of *X.*

Table 1. *VIF values of predictor variables in the generalized linear model (GLM) for CPUE*

Variable	GVIF	Df	GVIF $^{(1/(2*Df))}$
Year	1.242.195	1	1.114.538
Month	2.301.182	1	1.516.965
Season	4.402.548	2	1.448.525
SST	3.572.612	1	1.890.135
SSS	1.505.777	1	1.227.101
SSC	2.237.020	1	1.495.667
Moon Phase	1.041.749	3	1.006.840

*(GVIF= Generalized Variance Inflation Factor, Df=Degrees of freedom).

Table 2. The developed models and their corresponding AIC values

No	Model	AIC
1	CPUE~Year	1585
2	CPUE~Year+Month	1586
3	CPUE~Year+Month+Season	1584
4	CPUE~Year+Month+Season+SST	1586
5	CPUE~Year+Month+Season+SST+SSS	1588
6	CPUE~Year+Mont+Season+SST+SSS+SSC	1578
7	CPUE~Year+Month+Seson+SST+SSS+SSC+Moon Phases	**1571**

gladius. It was reported that *X. gladius* CPUE increased from the new moon phase with the lowest lunar index (0.0) to the full moon phase with the highest lunar index (1.0). Arifin et al. (2020) found that the highest catch amounts in pelagic fish caught by purse seines occurred during the first quarter lunar phase, while the lowest catches were observed during the new moon phase. Tosunoglu et al. (2021) reported that the lowest CPUE in sardine fishing with purse seine nets was observed during the full moon phase, while the highest CPUE occurred during the last quarter phase, and that CPUE decreased with increasing light intensity. In this study, the highest CPUE was also observed during the last quarter phase, and the lowest CPUE occurred during the full moon phase. These differences in findings across studies may be due to species-specific differences in

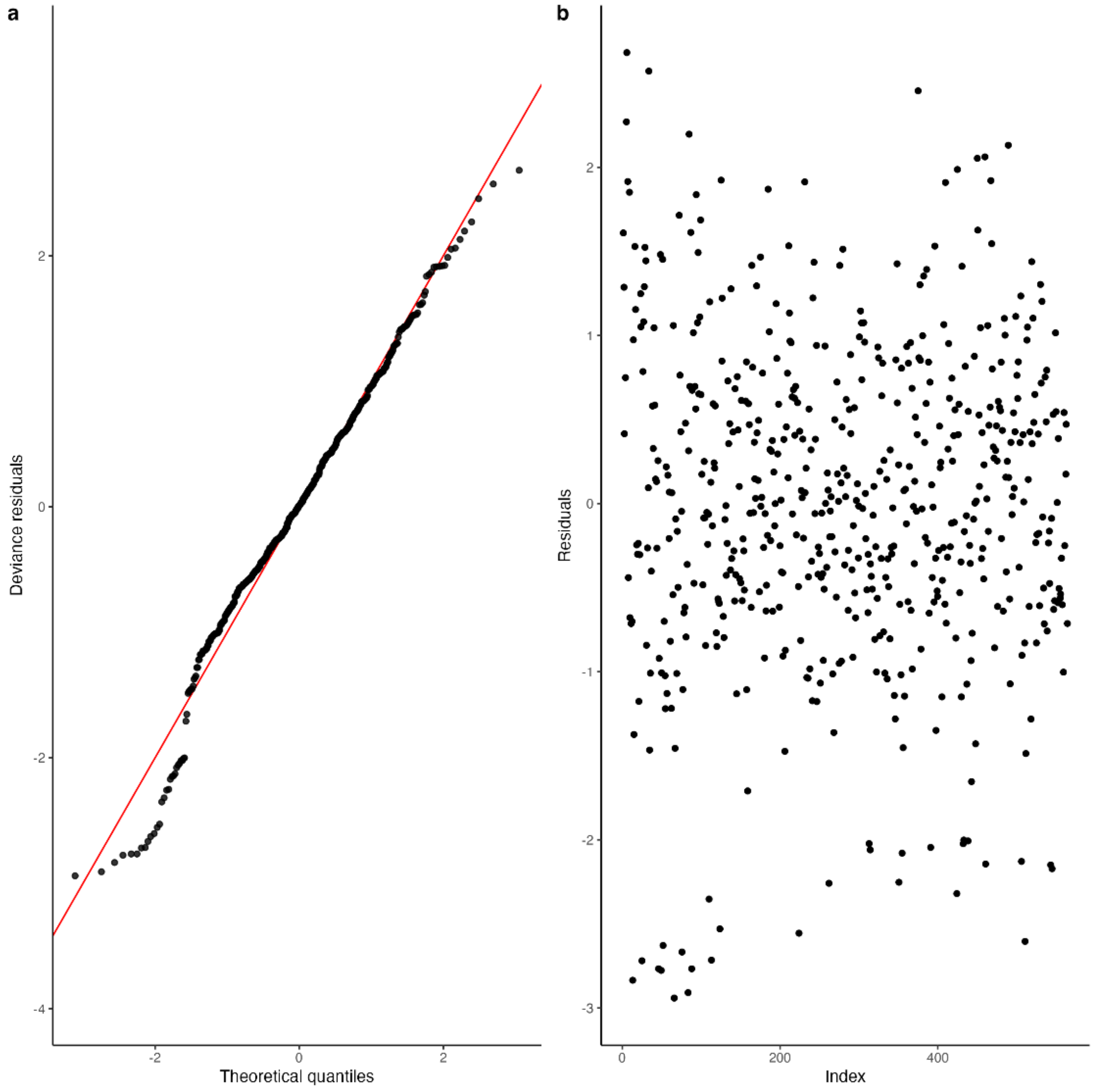

Figure 5. (a) QQ-plot of residuals (black). The red line indicates the 1–1 line. (b) Means of randomized quantile residuals.

Table 3 The significance test of explained variables in generalized linear

Explanatory Variable	Estimate	SE	t	*P*
Year	-0.0533	0.0210	-2.53	0.01
Month	-0.0112	0.0157	-0.716	0.474
SST	-0.0369	0.0241	-1.53	0.127
SSS	-0.166	0.258	-0.645	0.519
SSC	-1.73	0.499	-3.46	0.000589
Winter	-0.0490	0.163	-0.300	0.764
Spring	-0.371	0.192	-1.93	0.0537
First Quarter	-0.158	0.112	-1.41	0.159
Full Moon	-0.265	0.119	-2.22	0.0265
Last Quarter	0.135	0.108	1.25	0.213

*(SE= Standard Eror, t= t-statistic, *P*= probability value).

phototactic behaviors, habitats, feeding strategies, reproductive patterns, and the need for protection from predators. For instance, some fish exhibit positive phototaxis, moving toward light to feed on plankton, while others show negative phototaxis, moving away from light to feed or hide in deeper, darker waters. Although the effect of moonlight in this study was not statistically significant, fish that display phototactic behaviors tend to form schools in response to moonlight intensity, which can influence catch amounts (Jatmiko, 2015; Tosunoglu et al., 2021).

In the Aegean Sea, the use of artificial light is not merely a supplemental tactic—it is a fundamental component of purse seine fishing operations. Light boats are routinely deployed during nighttime fishing activities to attract schooling pelagic fish such as sardine and anchovy to the surface, where they can be encircled by the net. This artificial light can eliminate or change the effects of certain environmental factors, such as moonlight and chlorophyll-a. Recognizing the dominant role of artificial light in fishing success is essential for correctly interpreting the environmental drivers of CPUE in this fishery.

Tosunoglu et al. (2021) reported that SST values of 214 operations of a purse seine vessel operating in the Aegean Sea had a statistically significant positive effect on CPUE amounts. In addition, Liu et al. (2022) reported that there was a negative relationship between temperature and CPUE in the *Cololabis saira* fishery and that the order of importance of the affecting environmental factors was SST>SSS>SSC. In the Western Mediterranean, Jghab et al. (2019) reported a negative relationship between sardine catch and SST in a study covering 34 years of data. Leitão et al. (2018) reported an increase in SST over the years in their study conducted along the Portuguese coast, as well as significant increases in the catch of warmer water species by fishing gear. Sajna et al. (2019) reported that the CPUE of the important pelagic species *Sardinella longiceps* increased between 27 °C and 29 °C, while CPUE decreased at temperatures outside this range. Karakulak and Ceyhan (2024) found that the SST variable had no significant effects ($P>0.05$) on CPUE of the Atlantic bluefin tuna in the Eastern Mediterranean. In our study, SST also did not show a significant effect on CPUE. We think the findings may differ due to the difference in the optimal temperature ranges required for the species to survive.

Although SST is a well-known factor affecting feeding and shoaling behavior of anchovy and sardine, no statistically significant effect on CPUE was detected in this study. This may be due to the relatively narrow range of SST values observed during the fishing season (September–April), or the stronger influence of other operational factors such as lunar phase and artificial lighting. Additionally, SST may affect fish populations through lagged processes such as recruitment or migration timing, which are not directly reflected in daily CPUE values.

In the Western Mediterranean, Jghab et al. (2019) reported a significant negative relationship between sardine catch and SSS. Liu et al. (2022) reported a positive relationship between SSS and CPUE for *C. saira*. Maravelias and Reid (1997) reported that herring (*Clupea harengus*), a pelagic species in and around the Shetland Islands, are more abundant in surface waters with high salinity (>35 ppt). Sajna et al. (2019) reported a negative relationship between *S. longiceps* CPUE and SSS in Indian waters using GAM. In this study, we did not find a significant relationship between increasing salinity values and CPUE. We believe that a longer time series would provide more meaningful results for observing the relationship between salinity changes and CPUE.

The presence of phytoplankton and zooplankton in the stomachs and intestines of pelagic fish with a broad feeding spectrum (euryphagous) in their early stages indicates that they feed by filtering particles from the surrounding waters (Hunter, 1981; George et al., 2012). To examine the effect of chlorophyll-a concentration on the areas where fish larvae aggregate, Lasker (1975) placed *Engraulis mordax* larvae in water samples from different layers (from the surface and 15-30 m below the surface). It was found that larvae fed intensely in water samples with high chlorophyll concentration, while feeding in the surface water samples was minimal. This is consistent with the findings of George et al. (2012), who investigated the effect of chlorophyll-a concentration, obtained from satellite data, on *S. longiceps* catch rates in the coastal waters of three different states in India. They found that sardine larvae tended to form schools in response to increased chlorophyll levels. Additionally, it was observed that sardines arrived earlier in waters richer in chlorophyll, and a direct correlation between chlorophyll-a concentration and sardine catch rates was reported in each state. Similarly, Sajna et al. (2019) reported that chlorophyll-a had a positive relationship with the CPUE of *S. longiceps*. On the other hand, Liu et al. (2022) reported that annual *C. saira* CPUE was negatively correlated with SSC. In this study, we also found that SSC levels had a highly significant effect on CPUE, and there was a negative relationship between them.

Despite a moderate increase in chlorophyll-a levels over time, CPUE values declined. This negative relationship may be influenced by the widespread use of light boats in purse seine fisheries in the Aegean Sea, which can override natural environmental cues such as prey concentration. Artificial light strongly influences fish aggregation behavior, potentially weakening the direct link between primary productivity and catch rates. Moreover, seasonal misalignment between peak chlorophyll concentrations and fishing activity may also contribute to this decoupling.

Identifying the factors affecting fisheries and their impacts is crucial for the management of the oceans, which appear to be unlimited resources but are limited (Jatmiko, 2015; Nurlindah et al., 2017). This is because fisheries-dependent CPUE data are widely used to assess stocks (Ducharme-Barth et al., 2022). In order to reveal the effects of temporal and basic environmental factors (SST, SSC, SSS, dates, moon phases) on CPUE, we standardized the CPUE data using GLM. We think that the reason why some variables did not have significant effects on CPUE may be due to the lack of 2020 data, due to the COVID-19 pandemic.

Conclusion

This study shows that the pressure on fish stocks increases with decreasing CPUE over the years. In addition to temporal factors, CPUE is affected by environmental factors such as SSC. These changes need to be monitored more closely in order to provide an accurate guide to fisheries management. The fact that SSC has a statistically significant effect on CPUE while SST and SSS do not show significant effects emphasizes that fisheries are in complex interactions and the importance of species-specific studies with longer time series, especially in seas with high species diversity, such as the Mediterranean Sea.

Furthermore, as seen in other research, the variability in environmental effects depends on several factors such as target species, fishing gear, and region. Thus, a more comprehensive approach, including multiple fishing gears and environmental conditions, is essential for meaningful comparisons. The declining CPUE trend observed in our study points to an urgent need for more robust fisheries management and conservation efforts to safeguard the health of fish stocks in the Aegean Sea

Ethical Statement

Not applicable.

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Author Contribution

Cemre Balkı: Conceptualization, Writing -original draft, Data Curation, Resources, Investigation; Tevfik Ceyhan: Project manager, Data Curation, Formal Analysis, Methodology, Visualization and Writing - review and editing; Zafer Tosunoğlu: Data Curation, Writing -review and editing, Supervision. Ali Ulaş: Data Curation, Writing -review and editing, Supervision.

Conflict of Interest

The authors declare that they have no known competing financial or non-financial, professional, or personal conflicts that could have appeared to influence the work reported in this paper.

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