

Spatiotemporal variability in squid catch rates and their environmental associations in coastal waters of Langkawi and Kedah, Malaysia

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Abstract

Squid fisheries show strong spatial and temporal variability, while catch-per-unit-effort (CPUE)-environment relationships may be confounded by date and location. This study examined CPUE and environmental conditions in coastal waters of Langkawi and Kedah, northwestern Peninsular Malaysia, using 65 field observations collected on 13 sampling dates between November 2024 and November 2025. Five observations lacked chlorophyll-a measurements, leaving 60 for analysis. CPUE was standardized as catch weight per fishing hour and related to depth, temperature, salinity, pH and chlorophyll-a using Spearman correlation, Gamma generalized linear models (GLMs), a spatiotemporal Gamma generalized additive model (GAM), and Random Forest. Mean CPUE was $1.470 \pm 1.447 \text{ kg h}^{-1}$ and was strongly right-skewed. Chlorophyll-a showed the strongest pooled bivariate association with CPUE ($\rho = 0.629$, $p < 0.001$), but the relationship weakened within-date centering ($\rho = 0.227$, $p = 0.0818$), suggesting a strong temporal effect. The environmental-only GLM explained 40.4% of deviance, whereas the date-adjusted sensitivity model explained 82.0%. The spatiotemporal GAM explained 68.6% of deviance (EDoF = 11.01); the maximum CPUE observation yielded 64.1% explained deviance (EDoF = 10.98). Residual Moran's I detected no evidence of spatial autocorrelation across k-nearest-neighbour definitions from $k = 3$ to 6 ($p = 0.169$ – 0.291). Random Forest showed poor out-of-sample generalization under repeated and date-grouped cross-validation ($R^2 = -0.009$ and -0.023 , respectively). The results indicate that squid catch rates were affected by several interacting factors, including time, environmental conditions and location. Chlorophyll-a was the strongest measured environmental correlate. However, this association should be interpreted cautiously due to strong temporal effects.

1. Introduction

Marine fisheries and aquaculture contribute to food security, nutrition and livelihoods, and improving fisheries management is one of the central pillars of the Food and Agriculture Organization of the United Nations (FAO) Blue Transformation agenda (FAO, 2022). In Malaysia, the National Agrofood Policy 2021–2030 (NAP 2.0) likewise emphasizes sustainable fishing practices, research and development, governance and the use of data and technology in the fisheries and aquaculture sector (Ministry of Agriculture and Food Industries Malaysia, 2021). Within this broader management context, short-lived cephalopods require particular attention because their population dynamics and fishery availability can vary rapidly over relatively short temporal scales.

Cephalopods are characterized by rapid growth, short lifespans and substantial life-history plasticity. A global analysis of long-term time series reported increasing cephalopod abundance across diverse taxa and marine environments over six decades, although the authors attributed the pattern broadly to large-scale directional processes rather than identifying a single causal mechanism (Doubleday et al., 2016). These biological characteristics also complicate assessment and management: short lifespans, semelparous reproduction, high natural mortality, rapid growth and complex population structures can produce pronounced fluctuations in recruitment and fishery availability (Arkhipkin et al., 2021). For squid

fisheries, environmental variability is therefore especially relevant when interpreting changes in catch rates through space and time.

Evidence of such environmental sensitivity already exists for other neritic squid fisheries in the region, offering a useful comparative context for interpreting the present findings. Environmental associations have been documented for commercially exploited neritic squid in other western Pacific fisheries. For swordtip squid *Uroteuthis edulis* in northeastern Taiwan, Haghi Vayghan et al. (2024) used fishery, remotely sensed environmental and climate-index data in generalized additive models and reported monthly variation in catch rate and habitat suitability associated with oceanographic conditions. Earlier work on *U. edulis* in the southern East China Sea similarly examined variation in catch rate and distribution in relation to the oceanic environment (Liao et al., 2018). These studies demonstrate the value of incorporating environmental and temporal information into squid-fishery analyses, while also showing that habitat relationships may vary among regions, seasons and datasets.

Interpreting any such environmental signal in catch data, however, first requires clarifying what the underlying catch-rate metric represents. Catch per unit effort (CPUE) is commonly used to standardize fisheries catches for fishing effort, but it should not automatically be equated with absolute abundance. Comparative analyses have shown that CPUE is not necessarily proportional to true abundance, and changes in catchability can distort abundance signals (Harley et al., 2001). Fisheries-dependent catch rates may therefore reflect a combination of resource availability, fishing power, behaviour, location and environmental conditions; appropriate standardization and explicit treatment of spatial and temporal structure are important when CPUE is used for ecological inference (Bishop et al., 2008). This caution is particularly relevant to light-assisted squid fishing, for which the observed catch rate represents squid availability to the fishing operation rather than a direct census of population biomass.

A further analytical challenge arises when environmental, spatial and temporal variation occur simultaneously. A strong pooled association between an environmental variable and CPUE can partly reflect differences among sampling periods rather than a consistent relationship within each period. Flexible statistical models can also fit complex patterns in small datasets without necessarily providing reliable prediction for new observations. Generalized additive models (GAMs) are useful for representing non-linear relationships through penalized smooth functions while accommodating spatial and seasonal terms (Wood, 2017). Random Forest offers a complementary non-parametric predictive approach based on ensembles of randomized decision trees (Breiman, 2001), but its predictive performance must be evaluated on observations not used for model fitting. Separating explanatory modelling from out-of-sample predictive assessment is therefore important in data-limited, spatiotemporally structured fisheries studies.

Against this background, this study investigated spatiotemporal variability in squid CPUE across coastal fishing grounds of Langkawi and Kedah, northwestern Peninsular Malaysia, using observations collected on 13 sampling dates between November 2024 and November 2025. The objectives were to: (1) characterize spatial, temporal and environmental variability in squid CPUE; (2) quantify bivariate and

multivariate associations between CPUE and depth, temperature, salinity, pH and chlorophyll-a; (3) evaluate whether the pooled chlorophyll-a–CPUE relationship persisted after removing between-date variation; (4) model non-linear environmental, spatial and seasonal variation in CPUE using a spatiotemporal Gamma GAM and evaluate model sensitivity and residual spatial autocorrelation; and (5) assess out-of-sample predictive performance using Random Forest as a supplementary benchmark. The analysis was designed to distinguish measured environmental associations from broader spatiotemporal structure without treating CPUE as a direct measure of absolute squid abundance or inferring causal environmental thresholds from observational data.

2. Materials and Methods

2.1 Study Area and Squid Sampling

The study was conducted in the coastal waters surrounding Langkawi and adjacent Kedah, northwestern Peninsular Malaysia, within approximately 6.22–6.45°N and 99.64–99.88°E (Fig. 1). The sampling domain encompasses shallow coastal fishing grounds used by local fishers and includes spatial variation in bathymetry and proximity to islands and the mainland coast. Field observations were collected on 13 sampling dates between 30 November 2024 and 29 November 2025, generating 65 sampling observations distributed across the study area.

Squid sampling was conducted from a Class A fishing vessel measuring approximately 9 m in length and 2.5 m in width, powered by a 125 HP outboard engine and equipped with a 12 HP generator. Squid were attracted to the vessel using two green LED lights and one red halogen lamp positioned above the wheelhouse. Fishing was conducted using squid jigs and a cast net during nocturnal fishing operations. The cast net was approximately 4 m in length, produced an approximately 8 m spread when deployed, weighed approximately 10 kg, and was equipped with stainless-steel rings and lead sinkers. The net had a mesh size of approximately 1.5 inches and was constructed from approximately 0.3-mm nylon strand. Total squid catch obtained during each sampling operation was weighed and recorded in kilograms.

Fishing effort was recorded as the duration of each fishing operation. Because fishing duration varied among observations, raw catch weight was standardized as catch per unit effort (CPUE), calculated as $CPUE_i = C_i / E_i$, where C_i is squid catch (kg) at observation i and E_i is the corresponding fishing duration (h). CPUE was expressed as $kg\ h^{-1}$ and used as the biological response variable throughout the statistical analyses. CPUE was interpreted as an index of catch rate and squid availability to the fishing operation rather than as a direct measure of population abundance or biomass.

2.2 Environmental Data Collection and Chlorophyll-a Determination

In parallel with the biological sampling described above, environmental conditions were also characterized at each station. Environmental conditions were measured concurrently with squid sampling. Water depth (m) was recorded using an Erheng handheld depth sounder, while sea surface

temperature (°C), salinity and pH were measured in situ at each sampling location using field water-quality instrumentation. Geographic position was recorded as latitude and longitude and subsequently expressed in decimal degrees for spatial analysis.

For chlorophyll-a determination, approximately 1 L of seawater was collected at each sampling location using a Niskin water sampler and transported on ice for laboratory analysis. Water samples were filtered through 47-mm Whatman GF/F glass-fibre filters with a nominal pore size of 0.7 µm under vacuum. Each filter was folded with the retained material inward and immersed in 10 mL of 90% acetone. Samples were wrapped in aluminium foil and extracted for 24 h at 4°C in darkness. Following extraction, samples were centrifuged at 5,000 rpm for 10 min, and absorbance of the supernatant was measured spectrophotometrically at 630, 647, 664 and 750 nm. Absorbance at 750 nm was used to correct for turbidity, and chlorophyll-a concentration was calculated following Parsons et al. (1984):

$$\text{Chl-a} \left(\text{mg} \cdot \text{L}^{-1} \right) = \frac{[11.85 (A_{664} - A_{750}) - 1.54 (A_{647} - A_{750}) - 0.08 (A_{630} - A_{750})] \times v}{V \times L}$$

where A_λ is the absorbance measured at wavelength λ (nm), v is the volume of 90% acetone used for extraction (10 mL), V is the volume of seawater filtered (1.0 L), and L is the light path length of the cuvette (1.0 cm).

2.3 Data Preparation and Descriptive Analysis

Prior to formal statistical analysis, the combined biological and environmental dataset was compiled and screened as follows. The original dataset comprised 65 observations. Date and time information were standardized, and geographic coordinates recorded in degrees, minutes and seconds were converted to decimal degrees. Environmental variables included depth, temperature, salinity, pH and chlorophyll-a. Five observations lacked chlorophyll-a measurements and were treated as missing rather than as zero values. Consequently, analyses requiring the complete environmental predictor set were conducted using 60 complete observations.

The distribution of CPUE was characterized using the mean, median, standard deviation, variance, coefficient of variation, range, skewness and kurtosis. Distributional characteristics were visualized using histograms, kernel-density plots, boxplots and normal Q–Q plots. The Shapiro–Wilk test was additionally reported as a descriptive assessment of departure from normality. Because CPUE was continuous, strictly positive and strongly right-skewed, subsequent regression analyses used Gamma-family models with a log link rather than Gaussian-error models.

Observed CPUE was mapped using sampling longitude and latitude, with symbol size and colour scaled according to CPUE. Geographic boundaries were obtained from the GADM Malaysia boundary dataset and represented in WGS84 geographic coordinates (EPSG:4326). This map was used descriptively to visualize the geographic distribution of observed catch rates and was not treated as a formal spatial-clustering test.

2.4 Correlation and Multicollinearity Assessment

With these descriptive patterns established, attention then turned to how CPUE covaried with the measured environmental variables. Bivariate relationships between CPUE and environmental variables were evaluated using Spearman's rank correlation coefficient (ρ), which was selected because of the skewed distribution of CPUE and chlorophyll-a and the potential for non-linear monotonic relationships. Pairwise correlations were calculated among depth, temperature, salinity, pH, chlorophyll-a and CPUE.

Potential linear multicollinearity among environmental predictors was evaluated using variance inflation factors (VIF). VIF values were calculated for depth, temperature, salinity, pH and chlorophyll-a prior to multivariate modelling. VIF was used specifically as a diagnostic of linear collinearity and was not interpreted as evidence of statistical independence among predictors.

2.5 Temporal Structure and Within-Date Association

Beyond these pairwise associations, the temporal structure of the dataset required separate examination. Because observations were collected repeatedly between November 2024 and November 2025, temporal variation was explicitly examined rather than treating the dataset as a purely cross-sectional spatial survey. CPUE and environmental variables were summarized by sampling date to characterize temporal variation over the study period.

Particular attention was given to the association between chlorophyll-a and CPUE because preliminary analyses identified chlorophyll-a as the environmental variable most strongly correlated with CPUE. To distinguish the overall association from variation occurring among observations collected on the same date, chlorophyll-a and CPUE were centred within sampling date. For a variable X , the centred value was calculated as $X^*_{ij} = X_{ij} - \bar{X}_j$, where X_{ij} represents the observation at location i on sampling date j and $\bar{X}_j$ represents the corresponding date-specific mean. Spearman correlation was then calculated between within-date-centred chlorophyll-a and CPUE. Comparison of the pooled and within-date correlations was used to assess the extent to which the overall chlorophyll–CPUE association reflected between-date temporal covariation.

2.6 Gamma Generalized Linear Models

Having characterized bivariate and temporal patterns, multivariate models were then used to evaluate environmental associations with CPUE jointly. Gamma generalized linear models (GLMs) with a log link were fitted to examine multivariate associations between environmental conditions and CPUE. The environmental model included depth, temperature, salinity, pH and chlorophyll-a as predictors. In general form:

$$\log[E(\text{CPUE}_i)] = \beta_0 + \beta_1 \text{Depth}_i + \beta_2 \text{Temperature}_i + \beta_3 \text{Salinity}_i + \beta_4 \text{pH}_i + \beta_5 \text{Chl}_i.$$

A second model incorporated sampling date as a categorical fixed effect to evaluate whether associations between environmental variables and CPUE persisted after accounting for temporal

heterogeneity. Model performance was summarized using Akaike's Information Criterion (AIC) and explained deviance.

Because the number of sampling dates was relatively large in relation to the final sample size ($n = 60$), the date-adjusted GLM was treated as a temporal sensitivity analysis rather than as the principal inferential model. Furthermore, because sampling location varied among dates, temporal and spatial effects could not be assumed to be completely separable.

2.7 Random Forest Predictive Benchmark

As a non-parametric complement to the Gamma GLMs described above, out-of-sample predictive performance was also evaluated using Random Forest. A Random Forest regression model was fitted as a supplementary predictive benchmark using the measured environmental variables. Model performance was assessed using out-of-bag (OOB) R^2 , repeated cross-validation and date-grouped cross-validation. Predictive performance was summarized using R^2 , root mean squared error (RMSE) and mean absolute error (MAE).

Date-grouped cross-validation was included to provide a more stringent assessment of model generalization by preventing observations from the same sampling date from simultaneously contributing to model training and evaluation. Random Forest results were therefore interpreted as an assessment of out-of-sample predictive performance rather than as independent statistical validation of the GAM.

2.8 Spatiotemporal Generalized Additive Model

Beyond the linear and predictive frameworks described above, non-linear environmental, spatial and seasonal structure in CPUE was examined using a dedicated additive model. The principal model used to characterize non-linear environmental, spatial and seasonal variation in squid CPUE was a Gamma generalized additive model (GAM) with a log link. The model included penalized smooths for depth, temperature, salinity, pH and chlorophyll-a; a two-dimensional tensor-product smooth of longitude and latitude; and linear sine and cosine terms representing annual seasonal periodicity.

In general form:

$$\log[E(\text{CPUE}_i)] = \beta_0 + s_1(\text{Depth}_i) + s_2(\text{Temperature}_i) + s_3(\text{Salinity}_i) + s_4(\text{pH}_i) + s_5(\text{Chl}_i) + \text{te}(\text{Longitude}_i, \text{Latitude}_i) + \beta_6 \sin(2\pi \text{Month}_i/12) + \beta_7 \cos(2\pi \text{Month}_i/12).$$

Each environmental smooth was constrained to five basis functions to limit model flexibility given the relatively small sample size. The spatial tensor term used a 5×5 basis. Seasonal variation was represented using sine and cosine transformations of calendar month as linear terms, thereby modelling annual periodicity without introducing additional highly flexible smooths.

The model was implemented in Python using pyGAM (GammaGAM). Model performance was summarized using explained deviance, AIC and effective degrees of freedom (EDoF). Partial-dependence

curves with 95% confidence intervals were examined to characterize fitted environmental relationships.

Approximate term-level p-values generated by pyGAM were interpreted cautiously because smoothing-parameter estimation can produce anti-conservative significance estimates. Consequently, ecological interpretation emphasized effect shape, uncertainty, model diagnostics and consistency across complementary analyses rather than relying solely on individual smooth-term p-values.

2.9 Model Sensitivity and Residual Spatial Autocorrelation

This spatiotemporal GAM was then subjected to two further checks: sensitivity to the single most extreme observation, and diagnostic testing for residual spatial structure. Sensitivity of the final GAM to the most extreme observed catch rate was evaluated by removing the observation with the maximum CPUE and refitting the identical model specification to the remaining 59 observations. Explained deviance and EDoF were compared with those of the full-data model, together with the shapes of the fitted partial effects. Because the sensitivity model was fitted to a different dataset, differences in AIC between the full and reduced datasets were not used as evidence that one model was superior.

Potential residual spatial dependence was evaluated using Moran's I calculated from GAM residuals. Spatial neighbourhoods were defined using k-nearest-neighbour weights, with $k = 3, 4, 5$ and 6 , and statistical significance was evaluated using 9,999 permutations. Testing multiple neighbourhood definitions allowed the robustness of residual spatial dependence to be evaluated across alternative representations of local spatial connectivity.

The absence of a statistically significant Moran's I was interpreted as no evidence of residual spatial autocorrelation under the neighbourhood structures tested, rather than as proof of complete spatial independence.

2.10 Statistical Computing

Data processing, exploratory analyses, correlation analysis, GLMs, machine-learning evaluation, GAM fitting and spatial diagnostics were conducted in Python within Google Colaboratory. Principal packages included pandas and numpy for data management, scipy and statsmodels for statistical analysis, scikit-learn for Random Forest modelling and cross-validation, pyGAM for generalized additive modelling, and spatial-analysis libraries for Moran's I and geographic visualization. Statistical tests were evaluated at $\alpha = 0.05$, while exact effect estimates, confidence intervals and model-performance measures were emphasized over binary significance classifications.

3. Results

3.1 CPUE Distribution and Environmental Characteristics

Results are presented beginning with the overall distribution of CPUE and the measured environmental variables, before turning to spatial, temporal and multivariate patterns in the subsections that follow.

Analyses involving the complete environmental predictor set were based on 60 observations; five of the 65 field observations lacked chlorophyll-a measurements. Squid CPUE averaged 1.470 kg h⁻¹ (SD = 1.447), with a median of 1.038 kg h⁻¹ and a range of 0.154–8.077 kg h⁻¹. The coefficient of variation was 98.4%, indicating substantial variation in catch rates among observations. The CPUE distribution was strongly right-skewed (skewness = 2.590; excess kurtosis = 8.358), and the Shapiro–Wilk statistic was $W = 0.727$ ($p < 0.001$). These distributional features were reported descriptively and were consistent with the use of positive-response Gamma regression models in the subsequent analyses.

Environmental conditions varied unevenly across the dataset (Table 1). Depth ranged from 5.0 to 35.1 m (mean = 16.84 ± 5.87 m), consistent with the shallow coastal shelf character of the Langkawi–Kedah sampling domain described in Section 2.1 rather than a deeper offshore gradient, whereas temperature ($28.48 \pm 0.35^\circ\text{C}$), salinity (30.01 ± 0.22) and pH (8.012 ± 0.041) showed comparatively limited variation. Chlorophyll-a was substantially more variable, with a mean of 0.495 ± 0.721 in the units used in the analytical dataset, a median of 0.215, and a range of 0.110–4.231.

Table 1
Descriptive statistics for CPUE and measured environmental variables.

Variable	Mean	SD	Median	Minimum	Maximum	CV (%)
CPUE (kg h ⁻¹)	1.470	1.447	1.038	0.154	8.077	98.41
Depth (m)	16.838	5.871	15.700	5.000	35.100	34.87
Temperature (°C)	28.475	0.346	28.400	27.500	29.100	1.21
Salinity	30.005	0.217	30.000	29.500	30.800	0.73
pH	8.012	0.041	8.020	7.870	8.080	0.51
Chlorophyll-a*	0.495	0.721	0.215	0.110	4.231	145.69

3.2 Spatial Distribution of Observed CPUE

Beyond these pooled distributional characteristics, the spatial arrangement of observed catch rates was also examined. Observed CPUE was spatially heterogeneous across the Langkawi–Kedah sampling domain (Fig. 2). The largest observed catch rate occurred in the south-central portion of the sampled area, near approximately 99.72°E and 6.27°N, where the maximum CPUE was 8.077 kg h⁻¹. Several neighbouring observations also showed comparatively elevated catch rates, while another smaller group of moderate-to-high CPUE observations occurred farther east. Most observations in the northern portion of the sampling domain were comparatively low. These patterns describe the observed catch-rate distribution and were not treated as evidence of formally identified spatial hotspots.

3.3 Bivariate Environmental Associations and Multicollinearity

To assess how CPUE related to each environmental variable individually, and to check for redundancy among predictors, bivariate correlations and multicollinearity diagnostics were examined next. Among the measured environmental variables, chlorophyll-a showed the strongest bivariate association with CPUE (Spearman $\rho = 0.629$, $p < 0.001$). The remaining environmental variables showed weak and statistically non-significant bivariate associations with CPUE: depth ($\rho = 0.089$, $p = 0.499$), temperature ($\rho = 0.065$, $p = 0.620$), salinity ($\rho = -0.121$, $p = 0.356$) and pH ($\rho = 0.144$, $p = 0.274$). Among the environmental predictors themselves, salinity and pH were positively correlated ($\rho = 0.504$, $p < 0.001$), while chlorophyll-a was negatively correlated with salinity ($\rho = -0.354$, $p = 0.0055$) and depth ($\rho = -0.291$, $p = 0.0242$) (Table 2).

Variance inflation factors were low for all five environmental predictors: depth = 1.059, temperature = 1.081, salinity = 1.901, pH = 1.932 and chlorophyll-a = 1.082. These values provided no indication of problematic conventional linear multicollinearity in the predictor set; they were not interpreted as evidence that the predictors were statistically independent.

Table 2
Spearman rank correlations between CPUE and environmental variables.

Predictor	Spearman ρ	p-value	Result
Depth	0.089	0.4990	Weak; not statistically significant
Temperature	0.065	0.6204	Weak; not statistically significant
Salinity	-0.121	0.3563	Weak; not statistically significant
pH	0.144	0.2736	Weak; not statistically significant
Chlorophyll-a	0.629	< 0.001	Strongest measured bivariate association

3.4 Temporal Variation and Within-Date Chlorophyll-a Association

Because sampling spanned thirteen dates over a full annual cycle, temporal patterns in CPUE and in the chlorophyll-a association were examined next. CPUE varied substantially among sampling dates. The date-level summaries showed higher mean CPUE during the early part of 2025 and lower values during mid-2025; the highest date-level mean in the analysis occurred in January 2025 (approximately 4.22 kg h⁻¹), whereas July 2025 had a substantially lower mean (approximately 0.31 kg h⁻¹). These temporal summaries are descriptive because sampling locations also varied among dates.

The pooled chlorophyll-a–CPUE relationship was positive ($\rho = 0.629$, $p < 0.001$), but the association was substantially attenuated after both variables were centred within sampling date ($\rho = 0.227$, $p = 0.0818$). Thus, the within-date relationship was weaker and did not meet the $\alpha = 0.05$ significance criterion. This attenuation indicates that between-date temporal covariation contributed substantially to the stronger pooled chlorophyll-a–CPUE association.

3.5 Gamma Generalized Linear Models

These bivariate and temporal patterns were then evaluated jointly using multivariate Gamma GLMs. The environmental-only Gamma GLM explained 40.4% of the deviance (AIC = 144.34). Within this model, chlorophyll-a had a positive association with CPUE ($p < 0.001$), whereas salinity had a negative association ($p = 0.034$). The remaining measured environmental covariates were not statistically significant at $\alpha = 0.05$ in this model.

Including sampling date as a categorical fixed effect increased explained deviance to 82.0% (AIC = 89.88). In the date-adjusted model, depth ($p < 0.001$) and chlorophyll-a ($p = 0.035$) retained statistical associations with CPUE, and several date coefficients also differed from the reference date. Because the model used 13 sampling-date levels with only 60 complete observations, and because sampling date and geographic location were partially entangled, this model was treated as a temporal sensitivity analysis rather than as the principal inferential model.

3.6 Random Forest Predictive Performance

As a non-parametric counterpart to the GLM results, predictive performance was also assessed using Random Forest. The Random Forest model showed modest apparent performance under the out-of-bag criterion ($OOB R^2 = 0.302$), but this performance did not persist under resampling-based validation. Repeated cross-validation produced $R^2 = -0.009$, $RMSE = 1.118 \text{ kg h}^{-1}$ and $MAE = 0.726 \text{ kg h}^{-1}$. Under the more stringent date-grouped cross-validation, R^2 was -0.023 , $RMSE$ was 1.146 kg h^{-1} and MAE was 0.821 kg h^{-1} (Table 3). The negative cross-validated R^2 values indicate that the model did not outperform the corresponding mean-based prediction benchmark for held-out observations. Accordingly, Random Forest was retained as a supplementary predictive benchmark rather than as validation of the GAM.

Table 3
Random Forest predictive-performance metrics.

Evaluation	R ²	RMSE (kg h ⁻¹)	MAE (kg h ⁻¹)
Out-of-bag	0.3017	—	—
Repeated cross-validation	-0.0093	1.118	0.726
Date-grouped cross-validation	-0.0226	1.146	0.821

3.7 Spatiotemporal Gamma GAM

The principal spatiotemporal model, which represented non-linear environmental, spatial and seasonal structure simultaneously, is described next. The final spatiotemporal Gamma GAM, incorporating five environmental smooths, a two-dimensional longitude–latitude tensor term and seasonal sine/cosine terms, explained 68.6% of CPUE deviance. The model had an effective degrees of freedom (EDoF) of 11.01 and AIC = 131.05. These statistics indicate that the fitted model captured a substantial proportion

of the in-sample variation while using substantially fewer effective degrees of freedom than the nominal number of basis coefficients.

The pyGAM summary reported approximate term-level p-values for several terms, including temperature ($p = 0.046$), chlorophyll-a ($p < 0.001$), month sine ($p = 0.002$) and month cosine ($p < 0.001$). These values were not used as stand-alone evidence of ecological effects because pyGAM explicitly warns that p-values can be too small when smoothing parameters are estimated, causing the null hypothesis to be rejected too readily (pyGAM Developers, n.d.). Interpretation therefore emphasized the overall model fit, partial-effect shapes, uncertainty, complementary analyses and diagnostics rather than formal ranking of individual GAM terms.

3.8 Sensitivity Analysis and Residual Spatial Autocorrelation

The robustness of this model was then examined through a sensitivity analysis and tests for residual spatial autocorrelation. Excluding the maximum CPUE observation (8.077 kg h^{-1}) and refitting the same GAM specification to 59 observations yielded an explained deviance of 64.1% and EDoF = 10.98 (AIC = 125.26). The modest decline from 68.6% to 64.1% explained deviance indicates that the overall fit of the model was not dependent on the single maximum-CPUE observation. The AIC values of the full and sensitivity models were not used to rank the models because they were fitted to different datasets.

Residual spatial-autocorrelation tests were non-significant across all tested k-nearest-neighbour definitions. Moran's I was approximately 0.023 ($p = 0.290$) for $k = 3$, 0.015 ($p = 0.291$) for $k = 4$, 0.045 ($p = 0.169$) for $k = 5$ and 0.032 ($p = 0.181$) for $k = 6$. Thus, no evidence of residual spatial autocorrelation was detected under the tested neighbourhood structures. This result was not interpreted as proof of complete spatial independence.

Table 4
Final GAM performance, sensitivity analysis and residual Moran's I tests.

Analysis	n	Explained deviance	EDoF / Moran's I	AIC / permutation p
Full spatiotemporal Gamma GAM	60	0.6858 (68.6%)	EDoF = 11.01	AIC = 131.05
Sensitivity GAM (maximum CPUE excluded)	59	0.6413 (64.1%)	EDoF = 10.98	AIC = 125.26
Residual Moran's I, $k = 3$	60	—	I = 0.0233	p = 0.2904
Residual Moran's I, $k = 4$	60	—	I = 0.0153	p = 0.2907
Residual Moran's I, $k = 5$	60	—	I = 0.0449	p = 0.1691
Residual Moran's I, $k = 6$	60	—	I = 0.0324	p = 0.1812

3.9 Overall Results Synthesis

Collectively, the analyses showed pronounced spatiotemporal variation in squid CPUE. Chlorophyll-a was the strongest measured bivariate environmental correlate of CPUE, but its association was substantially weaker after removal of between-date variation. The date-adjusted GLM further indicated that temporal structure accounted for a large component of CPUE variability, while the final spatiotemporal GAM explained 68.6% of deviance and remained broadly stable after exclusion of the maximum observed CPUE. In contrast, the Random Forest showed poor out-of-sample generalization. Together, these results support a statistical description of CPUE as varying jointly with temporal, environmental and spatial structure rather than being attributable to a single measured environmental variable.

4. Discussion

4.1 Spatiotemporal variability in squid catch rates

Squid CPUE varied markedly across the Langkawi–Kedah sampling domain and through the 13 sampling dates, with a coefficient of variation of 98.4% and a strongly right-skewed distribution. Such variability is biologically plausible for cephalopod fisheries because many exploited cephalopods are short-lived, fast-growing and environmentally responsive, and their abundance and distribution can change rapidly among seasons and years (Rodhouse, 2010; Rodhouse et al., 2014; Arkhipkin et al., 2021). However, the present study measured fishery-dependent CPUE rather than absolute population abundance.

Commercial or artisanal catch rates can vary because of both animal availability and catchability, including spatial fishing patterns, gear performance and fishing conditions; consequently, raw CPUE should not be assumed to be directly proportional to stock abundance without appropriate standardization and supporting information (Bishop et al., 2008). This distinction is especially relevant here because squid were sampled with nocturnal light attraction, jigs and a cast net, so the response variable integrates biological occurrence with the probability that squid encountered and responded to the fishing operation.

The temporal signal was substantial. Mean CPUE was highest during the early part of 2025 and much lower during mid-2025, while the final spatiotemporal Gamma GAM included a clear annual seasonal component through sine and cosine month terms. The regional oceanographic literature provides a plausible environmental context for this pattern, but not a direct causal explanation. In the Malacca Strait, Mandal et al. (2021) documented strong monsoonal seasonality in surface chlorophyll-a, with markedly higher values during December–February than during May–September, and related that pattern to seasonal changes in winds, sea-surface temperature and upwelling-related processes. The timing is broadly consistent with the contrast observed in the present CPUE series. Nevertheless, currents, wind stress, prey fields and vertical water-column structure were not measured in this study; therefore, the observed seasonal CPUE pattern should be interpreted as a spatiotemporal association rather than evidence that monsoon forcing directly caused the catch-rate changes.

This cautious interpretation is also consistent with cephalopod ecology more generally. Environmental variability can influence recruitment, distribution, migration and life-cycle timing, but the direction and

magnitude of responses differ among species, life stages and regions (Rodhouse et al., 2014; Arkhipkin et al., 2021). For example, a South China Sea habitat study of *Sthenoteuthis oualaniensis* found strong seasonal habitat shifts associated with sea-surface temperature, chlorophyll-a and sea-surface height, but the chlorophyll relationship in that species and setting was negative rather than universally positive (Fan et al., 2021). Thus, environmental associations from other squid fisheries are useful ecological context but should not be transferred mechanistically to the unidentified multi-species catch in the present study.

4.2 Chlorophyll-a: the strongest measured correlate, but not a demonstrated causal driver

Of the patterns described above, the chlorophyll-a association merits particular scrutiny because it was the strongest measured signal in the dataset. Chlorophyll-a had the strongest measured bivariate association with CPUE in the pooled dataset (Spearman $\rho = 0.629$, $p < 0.001$), and it remained associated with CPUE in both the environmental-only Gamma GLM and the date-adjusted sensitivity model. This consistency makes chlorophyll-a an important covariate in the present dataset, but it does not establish chlorophyll-a as a direct biological driver of squid catch. Chlorophyll-a is widely used as an indicator of phytoplankton biomass, yet the relationship between chlorophyll concentration, phytoplankton carbon biomass and primary production is variable because pigment content changes with taxonomic composition, light, nutrients and temperature (Gui & Sun, 2024). It is therefore more accurate to treat chlorophyll-a here as an environmental indicator of the lower-trophic and hydrographic state of the sampled water rather than as a direct measure of prey available to squid.

The within-date analysis is central to this interpretation. After chlorophyll-a and CPUE were centred within sampling date, the correlation declined from $\rho = 0.629$ to $\rho = 0.227$ and was not statistically significant at $\alpha = 0.05$ ($p = 0.0818$). This attenuation indicates that a substantial part of the pooled association arose from differences among sampling dates rather than a consistent station-to-station relationship within individual dates. Regional evidence makes such temporal covariance plausible: chlorophyll-a in the Malacca Strait has a pronounced seasonal cycle associated with monsoonal physical forcing (Mandal et al., 2021). Consequently, a date with generally high chlorophyll-a can also coincide with generally high CPUE without requiring an immediate local trophic response at each station.

A food-web interpretation remains biologically plausible but was not tested directly. Cephalopods are active predators and their population dynamics can be affected by trophic conditions, yet the pathways linking primary production to cephalopod recruitment or fishery availability are complex and remain an important area of research (Rodhouse et al., 2014). The present study did not quantify zooplankton, forage fish, stomach contents or prey density, and it did not estimate a time lag between chlorophyll-a and squid response. Accordingly, statements that chlorophyll-a increased squid abundance through a specific prey-mediated mechanism would exceed the evidence. A defensible conclusion is that chlorophyll-a was the strongest measured environmental correlate of CPUE and also carried substantial temporal information about the sampling period.

4.3 Depth and the comparatively narrow hydrographic gradients

Attention now turns to the remaining environmental variables, beginning with depth. Depth showed little evidence of a simple monotonic relationship with CPUE in the bivariate analysis ($p = 0.089$, $p = 0.499$), yet it retained an association in the date-adjusted Gamma GLM. The difference between these analyses suggests that the role of depth cannot be reduced to a single unadjusted gradient. Depth may covary with location, habitat configuration, current exposure or the distribution of different squid life stages, and commercially exploited cephalopods commonly undertake spatial and ontogenetic movements between feeding and spawning habitats (Arkhipkin et al., 2021). In this dataset, however, species composition and maturity stage were not incorporated into the models. Depth should therefore be interpreted as a spatial-habitat covariate whose conditional association with CPUE warrants further investigation, rather than as evidence for a specific spawning depth or bathymetric optimum.

Temperature, salinity and pH showed weak bivariate relationships with CPUE, but the absence of strong correlations should not be interpreted as evidence that these variables are ecologically unimportant to squid. Their observed ranges were narrow, particularly for temperature (27.5–29.1°C), salinity (29.5–30.8) and pH (7.87–8.08), which limits the environmental contrast available for estimating response functions. Cephalopod growth, maturation, recruitment and distribution can respond to environmental variability, including temperature, but responses are species- and life-stage dependent (Rodhouse, 2010; Rodhouse et al., 2014; Arkhipkin et al., 2021). The present data therefore support only the narrower conclusion that these variables had limited explanatory signal over the range and sampling design observed here.

The low VIF values (all ≤ 1.932) indicate that conventional linear multicollinearity among the five environmental predictors was not severe. They do not, however, demonstrate ecological independence or exclude nonlinear dependence among predictors. This distinction is important for interpreting the GAM, where environmental variables can share seasonal and spatial structure even when linear VIF values are small.

4.4 Interpreting the spatiotemporal GAM and predictive benchmark

Having considered each environmental variable individually, the performance of the two multivariate modelling frameworks is considered next. The final Gamma GAM explained 68.6% of CPUE deviance with an effective degree of freedom of 11.01. This indicates a substantial in-sample representation of the observed spatiotemporal variation, but it should not be equated with independent predictive accuracy. The model combined environmental smooths, a two-dimensional spatial term and seasonal sine/cosine terms; these components are appropriate for representing nonlinear and spatially structured relationships, but the modest sample size ($n = 60$) and partial confounding of date with sampling location constrain how finely their contributions can be separated.

The sensitivity analysis strengthens one aspect of the model interpretation. After the maximum CPUE observation (8.077 kg h^{-1}) was removed, explained deviance decreased from 68.6% to 64.1% and EDoF changed only from 11.01 to 10.98. Thus, the broad level of fitted explanatory performance was not solely dependent on that single extreme catch-rate observation. This should not be described as proof of model robustness in all respects, because the sensitivity test addresses only one source of influence and does not substitute for external validation.

The Random Forest results provide a useful counterpoint. Its OOB R^2 was 0.302, but repeated and date-grouped cross-validation produced slightly negative R^2 values. Negative test-set R^2 indicates that predictions for held-out observations did not improve on the corresponding mean-based benchmark. The contrast between apparent in-sample or internal fit and held-out performance highlights the difficulty of prediction with a small, heterogeneous spatiotemporal dataset. It would nevertheless be inappropriate to conclude from these results that GAMs generally outperform Random Forests: the GAM and Random Forest were used for different analytical purposes, and the final GAM was not subjected to an equivalent external or date-grouped predictive evaluation in the present workflow. The defensible conclusion is simply that the Random Forest did not demonstrate reliable out-of-sample predictive skill for these data.

Approximate pyGAM term-level p-values were also treated conservatively. The official pyGAM documentation warns that when smoothing parameters are estimated, the reported p-values can be lower than they should be and may reject the null hypothesis too readily (pyGAM Developers, n.d.). For this reason, the discussion emphasizes effect patterns, complementary analyses, sensitivity testing and residual diagnostics rather than assigning ecological importance solely from the GAM significance codes.

4.5 Spatial pattern and residual spatial dependence

The spatial dimension of these results, and its statistical robustness, is considered next. The observed CPUE map showed a conspicuous high-catch observation and several comparatively elevated catches in the south-central part of the sampling domain, with another smaller group of moderate-to-high observations farther east. These are best described as areas of elevated observed CPUE rather than formal hotspots. No spatial point-pattern or hotspot statistic was applied to the observed catches, and the sampling design was not a spatially exhaustive survey. In addition, because CPUE is fishery dependent, a high mapped value can reflect local squid availability, catchability or both (Bishop et al., 2008).

Residual Moran's I values were non-significant across k-nearest-neighbour definitions from $k = 3$ to 6. This provides no evidence of residual spatial autocorrelation under the neighbourhood structures tested and is reassuring for the fitted model. It does not, however, prove that the spatial tensor term captured all ecologically meaningful spatial processes. Moran's I is conditional on the chosen residuals and spatial weights, while unmeasured processes can occur at spatial scales not represented by those neighbourhood definitions. The result should therefore be framed as a diagnostic indicating no

detectable residual spatial dependence under the tested specifications, rather than as confirmation of complete spatial independence.

4.6 Fisheries implications

Translating these statistical findings into fisheries management therefore requires care. The principal management value of the study is the identification of repeatable questions for monitoring rather than the delineation of permanent management zones. The data indicate that squid catch rates around Langkawi and Kedah can vary substantially over both space and time, and that environmental covariates—particularly chlorophyll-a—carry information about this variation. For short-lived cephalopods, rapid changes in recruitment, migration and availability can complicate conventional assessment and make frequent, seasonally resolved monitoring especially valuable (Rodhouse et al., 2014; Arkhipkin et al., 2021). In this context, repeated fishery-dependent CPUE observations combined with environmental measurements could contribute to an adaptive monitoring framework if sampling effort and catchability are standardized more rigorously.

The present map should not yet be used to designate a fixed high-productivity fishing ground, spatial closure or protected area. The apparent concentration of high CPUE in part of the study area requires confirmation across additional seasons and years, ideally with repeated sampling of the same spatial grid. Likewise, the seasonal CPUE pattern could be useful for planning future surveys, but it should not be translated directly into harvest advice without information on species composition, population structure, recruitment and fishing mortality. Reviews of cephalopod assessment emphasize that short life cycles, complex cohort structure and migration can make stock status difficult to infer from catch data alone (Rodhouse et al., 2014; Arkhipkin et al., 2021). Such a monitoring-first approach aligns with the broader emphasis on data-driven, adaptive fisheries governance articulated in the FAO Blue Transformation agenda and Malaysia's National Agrofood Policy 2021–2030, both of which were introduced at the outset of this study as the policy context motivating improved monitoring of short-lived, environmentally sensitive fishery resources (FAO, 2022; Ministry of Agriculture and Food Industries Malaysia, 2021).

4.7 Study limitations and priorities for future work

These implications must, in turn, be read against the limitations of the underlying dataset and analytical approach. Several limitations define the scope of inference. First, the final environmental analysis contained 60 complete observations distributed among 13 sampling dates. This is sufficient to identify strong patterns in the present dataset but remains limited for a model containing multiple nonlinear, seasonal and spatial components. Second, sampling date and geographic position were partially confounded because the same locations were not sampled uniformly on every date. Consequently, seasonal and spatial effects cannot be completely separated, even though both were represented in the GAM.

Third, the response variable was CPUE from a light-assisted artisanal fishing operation. Catchability was not independently estimated, and factors such as light response, gear efficiency, fisher deployment

decisions, lunar illumination, cloud cover, current speed and water clarity were not included. Fishery-dependent CPUE can be a useful relative index, but variation in catchability can distort its relationship with abundance (Bishop et al., 2008). Recording these operational covariates would materially improve future CPUE standardization.

Fourth, the analysis pooled squid catch because a fully documented species-identification protocol was not available for the statistical dataset used here. Environmental responses can differ among squid species, as illustrated by species-specific habitat relationships reported elsewhere (Fan et al., 2021). Future work should therefore pair standardized catch sampling with verified species identification and, where possible, mantle length, sex and maturity stage. This would allow environmental associations to be linked to biologically meaningful population components rather than to aggregated squid catch.

Fifth, the environmental measurements were concentrated on surface conditions and did not directly quantify prey fields, dissolved oxygen, turbidity, current velocity, water-column stratification or bottom-water conditions. Chlorophyll-a itself is an imperfect proxy for phytoplankton biomass and does not measure prey availability to squid directly (Gui & Sun, 2024). A stronger mechanistic design would combine repeated CPUE sampling with vertical hydrographic profiles, current measurements, zooplankton or forage-prey observations, and concurrent measures of water clarity and lunar conditions. Longer multi-year sampling would then allow the stability of seasonal and spatial relationships to be tested independently rather than inferred from a single annual cycle.

Overall, the evidence supports a conservative but ecologically informative conclusion: squid CPUE in the Langkawi–Kedah coastal fishery was strongly spatiotemporally structured during the study period; chlorophyll-a was the strongest measured environmental correlate, but much of that relationship was associated with between-date variation; and a nonlinear spatiotemporal GAM captured a substantial fraction of observed variation without evidence of residual spatial autocorrelation under the tested neighbourhood definitions. These findings provide a quantitative foundation for a larger, species-resolved and more fully standardized monitoring programme, but they do not by themselves establish causal environmental mechanisms, absolute abundance, permanent spatial hotspots or stock status.

5. Conclusion

This study demonstrates that squid catch rates in the coastal waters of Langkawi and Kedah are characterized by substantial spatial, temporal, and environmental variability. Among the environmental variables examined, chlorophyll-a showed the strongest pooled association with CPUE; however, this relationship weakened considerably after between-date variation was removed. This finding indicates that the apparent chlorophyll-a–CPUE relationship cannot be interpreted independently of temporal structure and cautions against attributing squid availability to a single environmental factor.

The spatiotemporal Gamma GAM provided a useful framework for representing the combined non-linear environmental, spatial, and seasonal structure in the data, explaining 68.6% of CPUE deviance. Its overall performance remained broadly similar after exclusion of the maximum CPUE observation, while residual

analyses detected no evidence of spatial autocorrelation across the tested neighborhood specifications. In contrast, Random Forest showed poor performance under repeated and date-grouped cross-validation, highlighting the importance of evaluating predictive models using genuinely held-out observations, particularly when sample sizes are limited and observations are temporally structured.

Collectively, the findings indicate that squid CPUE in this tropical coastal fishery reflects interacting environmental and spatiotemporal processes rather than the influence of a single dominant environmental variable. The observed areas of elevated CPUE should therefore be regarded as temporally contingent fishing areas rather than persistent biological hotspots until they are validated through more extensive sampling. Future studies should incorporate larger multi-year datasets, more balanced spatial sampling among dates, subsurface oceanographic measurements, species- and life-stage information, and independent model validation. Such improvements would help determine whether the patterns identified here persist across seasons and years and strengthen the evidence base for environmentally informed management of coastal squid fisheries in northwestern Peninsular Malaysia.

Declarations

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Author Contribution

Author 1 responsible for wrote the main manuscript text, author 2 wrote the method and provide data for this research. Author 3 - 5 contribute to data collection of this project.

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References

1. Arkhipkin AI, Hendrickson LC, Payá I, Pierce GJ, Roa-Ureta RH, Robin J-P, Winter A (2021) Stock assessment and management of cephalopods: Advances and challenges for short-lived fishery resources. *ICES J Mar Sci* 78(2):714–730. <https://doi.org/10.1093/icesjms/fsaa038>

2. Bishop J, Venables WN, Dichmont CM, Sterling DJ (2008) Standardizing catch rates: Is logbook information by itself enough? ICES J Mar Sci 65(2):255–266.
<https://doi.org/10.1093/icesjms/fsm179>
3. Breiman L (2001) Random forests. Mach Learn 45:5–32. <https://doi.org/10.1023/A:1010933404324>
4. Doubleday ZA, Prowse TAA, Arkhipkin A, Pierce GJ, Semmens J, Steer M, Leporati SC, Lourenço S, Quetglas A, Sauer W, Gillanders BM (2016) Global proliferation of cephalopods. Curr Biol 26(10):R406–R407. <https://doi.org/10.1016/j.cub.2016.04.002>
5. Fan J, Chen Z, Feng X, Yu W (2021) Climate-related changes in seasonal habitat pattern of *Sthenoteuthis oualaniensis* in the South China Sea. Ecosyst Health Sustain 7(1):1926338. <https://doi.org/10.1080/20964129.2021.1926338>
6. Food and Agriculture Organization of the United Nations (FAO) (2022) The State of World Fisheries and Aquaculture 2022: Towards Blue Transformation. FAO. <https://doi.org/10.4060/cc0461en>
7. Gui J, Sun J (2024) Phytoplankton carbon to chlorophyll a model development: A review. Front Mar Sci 11:1466072. <https://doi.org/10.3389/fmars.2024.1466072>
8. Haghi Vayghan A, Ray A, Mondal S, Lee M-A (2024) Modeling of swordtip squid (*Uroteuthis edulis*) monthly habitat preference using remote sensing environmental data and climate indices. Front Mar Sci 11:1329254. <https://doi.org/10.3389/fmars.2024.1329254>
9. Harley SJ, Myers RA, Dunn A (2001) Is catch-per-unit-effort proportional to abundance? Can J Fish Aquat Sci 58(9):1760–1772. <https://doi.org/10.1139/f01-112>
10. Liao C-H, Lan K-W, Ho H-Y, Wang K-Y, Wu Y-L (2018) Variation in the catch rate and distribution of swordtip squid *Uroteuthis edulis* associated with factors of the oceanic environment in the southern East China Sea. Mar Coastal Fisheries 10:452–464. <https://doi.org/10.1002/mcf2.10039>
11. Mandal S, Behera N, Gangopadhyay A, Susanto RD, Pandey PC (2021) Evidence of a chlorophyll tongue in the Malacca Strait from satellite observations. J Mar Syst 223:103610. <https://doi.org/10.1016/j.jmarsys.2021.103610>
12. Ministry of Agriculture and Food Industries Malaysia (2021) National Agrofood Policy 2021–2030 (NAP 2.0). Government of Malaysia
13. Parsons TR, Takahashi M, Hargrave B (1984) Biological oceanographic processes (3rd ed.). Pergamon Press. <https://doi.org/10.1016/C2009-0-07690-9>
14. pyGAM Developers. (n.d.). Quick start. pyGAM documentation. Retrieved September 22 (2026) from https://pygam.readthedocs.io/en/stable/notebooks/quick_start.html
15. Rodhouse PG (2010) Effects of environmental variability and change on cephalopod populations: An introduction to the CIAC '09 Symposium special issue. ICES Journal of Marine Science, 67(7), 1311–1313. <https://doi.org/10.1093/icesjms/fsq084>
16. Rodhouse PGK, Pierce GJ, Nichols OC, Sauer WHH, Arkhipkin AI, Laptikhovsky VV, Lipiński MR, Ramos JE, Gras M, Kidokoro H, Sadayasu K, Pereira J, Lefkaditou E, Pita C, Gasalla M, Haimovici M, Sakai M, Downey N (2014) Environmental effects on cephalopod population dynamics: Implications

17. Wood SN (2017) Generalized additive models: An introduction with R, 2nd edn. CRC

Figures

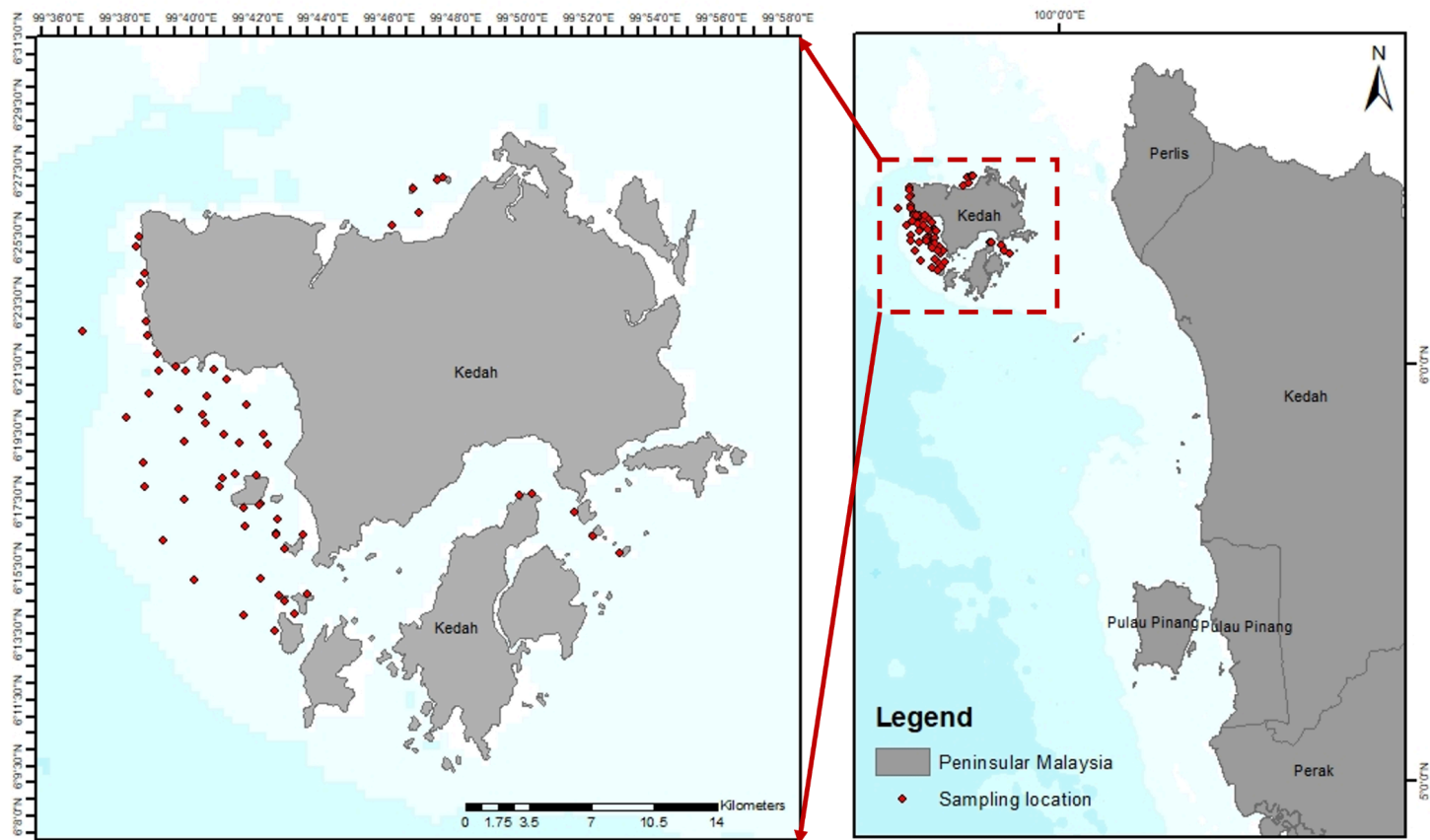


Figure 1

Squid sampling stations around Langkawi and Kedah waters.

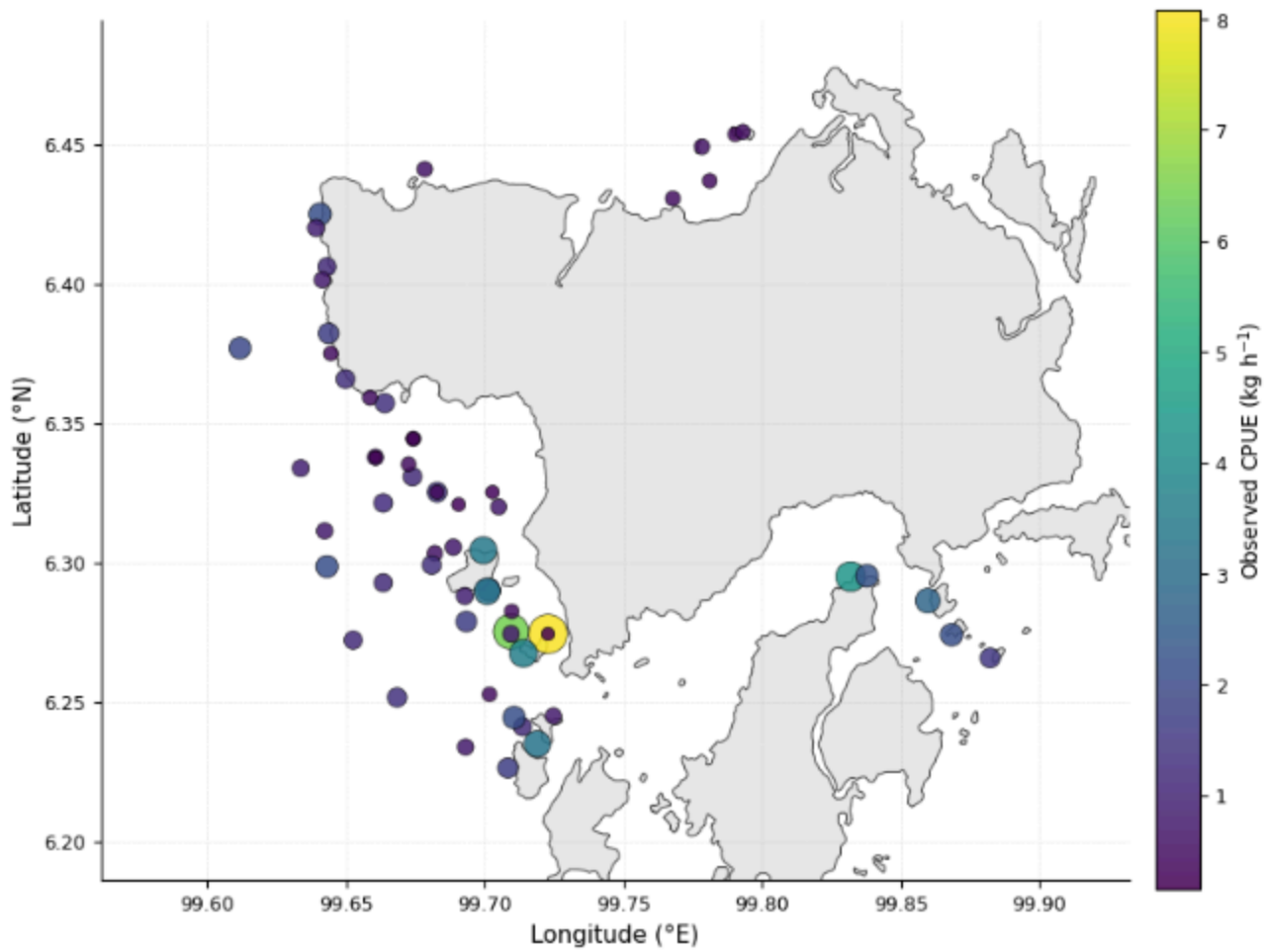


Figure 2

Spatial distribution of observed squid catch per unit effort (CPUE) across sampling locations in coastal waters of Langkawi and Kedah, Peninsular Malaysia. Symbol colour represents observed CPUE (kg h^{-1}), while symbol size is scaled to facilitate visualization of variation among sampling locations.