

Review

Advances in Remote Sensing-Based Studies on Environmental Characteristics and Formation Mechanisms of Purpleback Flying Squid Fishing Grounds

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Abstract

The purpleback flying squid (*Sthenoteuthis oualaniensis*) is an important commercially exploited cephalopod resource in tropical open oceans. The formation and spatial variability of its fishing grounds are jointly regulated by local marine environmental conditions, ocean dynamic processes, and multiscale climate variability. In recent years, substantial progress has been achieved in understanding the environmental characteristics and formation mechanisms of *S. oualaniensis* fishing grounds with the development of satellite remote sensing, multisource oceanographic observations, and ecological statistical models. However, due to differences in study regions, data sources, and modeling approaches, considerable discrepancies remain among studies regarding the mechanisms through which environmental factors and climate modes influence the distribution and abundance variations in *S. oualaniensis* resources. This review systematically summarizes recent advances in the application of remote sensing and multisource marine data in *S. oualaniensis* fishing ground studies and highlights the ecological significance of major environmental drivers. Current evidence indicates that the formation of *S. oualaniensis* fishing grounds is not controlled by a single environmental factor but results from the integrated effects of SST, Chl-a, oceanographic dynamic processes (e.g., mesoscale eddies, fronts, and upwelling), and subsurface environmental conditions such as thermocline structure and dissolved oxygen. Suitable thermal conditions and moderate productivity levels provide fundamental environmental prerequisites for resource aggregation, whereas mesoscale physical processes and three-dimensional ecological structures further regulate prey transport, habitat availability, and squid aggregation processes. Moreover, substantial regional differences exist in fishing ground formation mechanisms. In the northwestern Indian Ocean, fishing grounds are primarily controlled by monsoon-driven upwelling and large-scale circulation systems, exhibiting strong continuity and pronounced climate-related variability. In contrast, fishing grounds in the South China Sea are more strongly influenced by Kuroshio intrusion, island–reef topography, and regional circulation processes, resulting in greater spatial heterogeneity. With advances in analytical approaches, fishing ground prediction methods for *S. oualaniensis* have gradually evolved from empirical statistical analyses toward multifactor statistical modeling and machine-learning-based prediction frameworks. Nevertheless, resolving three-dimensional ecological processes, developing physical–biological coupled models, and improving model interpretability remain key challenges for future



Academic Editor: José Lino Costa

Received: 8 June 2026

Revised: 29 July 2026

Accepted: 29 July 2026

Published: 3 August 2026

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research. This review provides theoretical insights for remote sensing-based investigations of *S. oualaniensis* fishing ground formation mechanisms, resource assessment, and sustainable exploitation.

Keywords: *S. oualaniensis* fishing grounds; formation mechanisms; environmental factors; climate modes; remote sensing technology

Key Contribution: The major contributions of this review are summarized as follows: (1) We systematically reviewed the applications of remote sensing, multisource oceanographic observations, and fisheries data in *S. oualaniensis* fishing ground studies, and compared the advantages and limitations of different data sources for environmental characterization and resource monitoring. (2) We identified the key environmental factors affecting fishing ground formation and summarized the multiscale ecological regulation mechanisms, revealing the interactions among local environmental conditions, ocean dynamic processes, and climate anomalies. (3) We compared regional differences in fishing ground formation mechanisms between the northwestern Indian Ocean and the South China Sea, emphasizing the regulating roles of oceanographic dynamics and ecosystem structure in resource distribution. (4) We summarized recent developments in remote sensing integration and ecological prediction models, and proposed future research priorities including three-dimensional ecological processes, physical–biological coupled modeling, and intelligent prediction approaches.

1. Introduction

The purpleback flying squid, commonly known as the red squid or southern squid, belongs to the class Cephalopoda, order Teuthoidea, family Ommastrephidae, and genus *Sthenoteuthis* [1], and is widely distributed across the tropical and subtropical waters of the Indian and Pacific Oceans [2,3], including the South China Sea (SCS). Characterized by biological traits such as a short lifespan, rapid growth, generation turnover, and high population recruitment capacity, it has become one of the primary strategic species targeted for development in global distant-water fisheries [4,5]. As a key species in epipelagic marine ecosystems, *S. oualaniensis* plays a crucial “mediator” role in food web structures. It preys on other cephalopods, small fishes, and crustaceans, while conversely serving as a vital prey source for tunas, sharks, and marine mammals, which is of great significance for maintaining energy transfer and material cycling in marine ecosystems [6,7]. In recent years, *S. oualaniensis* has emerged as a cornerstone of China’s tropical oceanic fisheries in regions such as the Northwest Indian Ocean and the South China Sea. The scale of its resource exploitation and its economic value have continuously expanded, demonstrating immense potential for fishery utilization.

S. oualaniensis exhibits distinct ecological characteristics, including a broad distribution range and pronounced diel vertical migration (DVM), with its populations demonstrating clear seasonal aggregation and spatial shift patterns [8]. Traditional vessel-based surveys and fishery statistics mainly rely on point observations or limited sampling, which are costly and constrained by limited spatial and temporal coverage. Consequently, they are insufficient for systematically capturing the dynamic formation and evolution of *S. oualaniensis* fishing grounds (i.e., spatial areas characterized by concentrated commercial fishing activities and high catch yields). These methods suffer from high costs and restricted spatiotemporal coverage, making it challenging to systematically characterize the dynamic processes of fishing ground formation and evolution. With the advancement of satellite remote sensing technology, key environmental variables—such as Sea Surface Temperature

(SST), Chlorophyll-a concentration (Chl-a), Sea Surface Height (SSH), Sea Surface Salinity (SSS), and Sea Surface Height Anomaly (SSHA)—can now be monitored across large scales, quasi-synchronously, and over long time series. This provides an indispensable tool for revealing the spatial patterns and environmental backgrounds of *S. oualaniensis* fishing grounds [9]. Remote sensing observations have broken through the limitations of traditional “point-based surveys,” enabling a leap in fishing ground research from local to regional scales, and from discrete to continuous observations [10,11].

A wealth of research indicates that *S. oualaniensis* is highly sensitive to marine environmental changes, and its fishing ground distribution is regulated by multi-scale coupling of thermal structures, biological productivity, and marine dynamic processes [12–15]. Physical processes, including monsoon circulation, mesoscale eddies, water mass structures, and frontal systems, further modify feeding and spawning environments by influencing sea surface temperature, mixed-layer depth, and nutrient transport [16,17]. Concurrently, global climate modes, such as the El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD), further reshape the interannual and decadal patterns of fishing grounds by modulating air–sea interactions and large-scale circulation structures [18]. Driven by the accumulation of remote sensing data and enhancements in computational power, methodologies for studying *S. oualaniensis* fishing grounds have continuously evolved. Fishing ground prediction approaches have gradually evolved from early methods based on environmental suitability assessment and empirical statistical analyses to integrated modeling frameworks that incorporate multisource remote sensing data, climate indices, and reanalysis products. In recent years, the application of machine learning and deep learning approaches in fishing ground prediction studies has increased substantially, improving the capability to simulate and predict resource distributions under complex environmental conditions and promoting a transition from empirical assessments toward intelligent prediction [19].

Despite significant progress in remote sensing-based research on *S. oualaniensis* fishing grounds, existing studies mostly focus on specific sea areas, single environmental factors, or a single category of prediction models [20–22]. Against the background of global climate change and rapid developments in ocean observation technologies, understanding how remote sensing approaches can be used to elucidate the formation mechanisms and spatiotemporal dynamics of *S. oualaniensis* habitats (defined as environmental spaces characterized by specific physical and biological conditions) has become a key research priority. Therefore, this review focuses on remote sensing-based environmental data sources, spatiotemporal characteristics of fishing grounds, environmental driving mechanisms, regional differences, and the evolution of fishing ground prediction models. Special attention is given to the northwestern Indian Ocean and the South China Sea. The objective of this review is to systematically summarize recent advances in the application of remote sensing technologies in *S. oualaniensis* fishing ground studies and to provide theoretical foundations and methodological references for resource assessment, fishing ground forecasting, and sustainable exploitation under future climate change scenarios.

2. Remote Sensing Environmental Variables for Fishing Ground Analysis: Data Sources, Uncertainties, and Scientific Contributions

2.1. Multisource Remote Sensing and Fisheries Observation Data Foundations

With the development of satellite remote sensing, ocean reanalysis, and fisheries information technologies, studies on *S. oualaniensis* fishing grounds have gradually established an observational framework centered on the integration of multisource heterogeneous datasets [23,24]. These datasets mainly include sea surface remote sensing observations, three-dimensional ocean reanalysis products, and fisheries observation data,

which are used to characterize marine environmental conditions across different spatial and temporal scales.

For sea surface environmental observations, variables including SST, Chl-a, SSH, SSS, and surface wind fields are among the most widely used environmental factors in contemporary fishing ground studies [25]. These datasets are primarily derived from satellite-based retrieval products generated by multiple sensors, such as MODIS, AVHRR, and VIIRS [26–28]. Among them, moderate-resolution sensors such as MODIS have been extensively applied in analyses of interannual fishing ground variability and climate-driven responses due to their long-term observational records [29]. In contrast, VIIRS provides advantages for fine-scale fishing ground identification and short-term dynamic monitoring owing to its higher spatial resolution [30]. Regarding ocean dynamics and three-dimensional environmental structures, satellite altimetry datasets (e.g., AVISO) and ocean reanalysis products (e.g., HYCOM, ECCO, and CMEMS systems) provide essential support for investigating subsurface ocean processes [31–33]. These datasets provide three-dimensional environmental information, including temperature, salinity, ocean currents, and mixed-layer depth (MLD), which facilitates the characterization of ocean dynamic structures and energy transport processes [34]. Furthermore, the incorporation of biogeochemical variables, such as dissolved oxygen (DO), further improves the representation of ecological constraints in marine environments, extending habitat studies from two-dimensional surface conditions to three-dimensional ecological spaces [35–37]. Regarding fisheries observations and vessel activity data, Automatic Identification System (AIS), Vessel Monitoring System (VMS), and GPS trajectory data provide fundamental spatiotemporal information on fishing vessel operations [38,39]. However, conventional fisheries statistics remain subject to certain limitations due to incomplete data coverage and statistical uncertainties. In recent years, VIIRS nighttime light remote sensing data (Day/Night Band, DNB) have been widely applied for identifying nighttime fishing vessels and validating fishing activities, thereby improving the completeness and reliability of fisheries activity information [40].

Consequently, the integration of multi-source data has become a key trend in current fisheries research, centring on utilising the complementary characteristics of different data sources to achieve a comprehensive, multi-scale and multi-dimensional characterisation of marine ecosystems. Table 1 summarises the types, application scenarios and comparative advantages of multi-source remote sensing and fisheries observation data.

Table 1. Comparison of multisource remote sensing and fisheries observation datasets, applications, and advantages.

Data Type	Main Data Sources	Application Scenarios	Main Applications	Advantages	Data Access
Sea surface remote sensing data (SST, Chl-a, SSH, SSS, etc.)	MODIS/AVHRR/VIIRS/CMEMS	MODIS: long-term climate variability analysis; VIIRS: high-resolution short-term fishing ground identification; CMEMS: continuous spatiotemporal environmental reconstruction	Identification of fishing ground spatial distribution; analysis of environmental drivers; HSI/SDM modeling	Long-term time series, extensive spatial coverage, and capability for large-scale monitoring of fishing ground dynamics	NASA Ocean Color Web; NASA Earthdata Search; NOAA NCEI & CoastWatch; Copernicus Marine Service
Three-dimensional ocean reanalysis data	HYCOM/ECCO/CMEMS reanalysis products/AVISO	HYCOM/ECCO: analysis of three-dimensional ocean structures and dynamic mechanisms; AVISO: SSH and mesoscale eddy identification	Vertical habitat modeling; analysis of diel vertical migration mechanisms	Provide continuous three-dimensional environmental fields and compensate for the limitations of surface-based remote sensing observations	Copernicus Marine Data Store; HYCOM Data Server; AVISO+ CNES Data Center

Table 1. Cont.

Data Type	Main Data Sources	Application Scenarios	Main Applications	Advantages	Data Access
Fisheries observation and vessel activity data (AIS/VMS/GPS)	Vessel monitoring systems and vessel tracking data	AIS/VMS: continuous trajectory analysis; GPS: high-precision local fishing operation information	Fishing effort analysis; CPUE estimation; fishing ground validation	Provide actual fishing operation data and support model validation	Global Fishing Watch
Nighttime and microwave remote sensing auxiliary data (DNB/SAR, etc.)	VIIRS DNB/Sentinel-1 SAR	DNB: identification of fishing vessels based on nighttime light intensity; SAR: all-weather vessel detection	Fishing vessel identification; illegal fishing monitoring; validation of fishing activities	Independent verification of fishing activity distribution with minimal influence from cloud cover	Payne Institute Earth Observation Group (EOG); NASA Worldview

2.2. Data Uncertainties, Potential Biases, and Limitations

Although the integration of multi-source remote sensing and fisheries observational data has enabled squid fishing-ground studies to incorporate multiple environmental dimensions, including thermal conditions, primary productivity, and ocean dynamics [35,41], uncertainties remain during data acquisition and processing.

The first major limitation involves satellite remote sensing uncertainties and data gaps. Both the Northwest Indian Ocean and the South China Sea are strongly influenced by monsoon systems, during which increased cloud cover and atmospheric disturbances can cause missing observations or retrieval uncertainties in satellite-derived products such as SST and Chl-a [42,43]. Because these periods often coincide with enhanced upwelling, productivity variations, and fishing-ground redistribution, data gaps may reduce the ability to capture temporal changes in suitable habitats of *S. oualaniensis* (defined as areas where environmental conditions fall within the optimal ranges of key habitat variables). Second, the smoothing effects and resolution limitations of ocean reanalysis products may constrain the representation of the three-dimensional ecological niche of *S. oualaniensis*. Although products such as CMEMS, HYCOM, and ECCO provide assimilated three-dimensional ocean fields, uneven distributions of in situ observations (e.g., Argo floats) can introduce uncertainties in vertically structured variables such as mixed-layer depth (MLD) and dissolved oxygen (DO) [44,45]. Given the pronounced diel vertical migration of *S. oualaniensis*, these uncertainties may influence assessments of its vertical habitat range. Third, mismatches in spatial and temporal scales between environmental data and fisheries observations remain a challenge for fishing-ground prediction. Remote sensing products generally have kilometer-scale resolution, whereas fishing operations occur at much finer spatial scales. Consequently, catch data are often aggregated into grids during data integration, which may smooth local environmental heterogeneity associated with fronts, eddies, and other mesoscale processes. Such scale mismatches may limit the identification of fine-scale habitat preferences and aggregation mechanisms of *S. oualaniensis* [46]. Finally, fisheries data are affected by sampling biases and CPUE uncertainties. AIS/VMS trajectories and commercial catch data are not randomly distributed but are concentrated in historically productive areas and traditional fishing grounds. This issue is particularly relevant to the light-attraction fishery of *S. oualaniensis*, where fleet operations are influenced by previous fishing experience, sea conditions, and economic factors. Therefore, fishing hotspots may reflect both squid aggregation and fishing behavior rather than resource distribution alone [47]. In addition, CPUE can be affected by differences in fishing gear, operational strategies, and fishing efficiency, requiring standardization approaches such as GLMs to improve the reliability of abundance estimates [48,49].

2.3. Scientific Contributions of Satellite Information to *S. oualaniensis* Research

Despite the aforementioned uncertainties, multisource satellite remote sensing and fisheries observation data are widely recognized as essential tools for understanding the spatial distribution mechanisms of pelagic and mesopelagic migratory species. Their scientific contributions can be summarized into three major aspects. First, satellite-derived environmental information has been widely applied in modeling analyses of fishing grounds driven by oceanographic conditions. Previous studies have demonstrated that variables such as SST, Chl-a, and SSH can effectively explain spatial variations in the distribution of *S. oualaniensis* and other epipelagic and mesopelagic cephalopods. These environmental variables have been extensively incorporated into habitat modeling approaches, including generalized additive models (GAMs), maximum entropy models (MaxEnt), and random forest algorithms [50]. Second, satellite observations enable the characterization of nonlinear responses between environmental variables and species distributions. Studies have shown that in dynamic oceanographic environments, such as frontal systems and mesoscale eddy fields, variations in SST and Chl-a can induce nonlinear responses in the spatial distribution patterns of *S. oualaniensis* [21]. Finally, satellite remote sensing technologies have substantially enhanced the capability to monitor fishing activities. The integration of VIIRS nighttime light remote sensing data (DNB) with AIS/VMS datasets has been applied to identify light-assisted purse seine fishing activities and improve the reliability of fishing effort estimation. This approach has become one of the important directions in current remote sensing studies of offshore fisheries [39,51].

3. Spatiotemporal Characteristics of *S. oualaniensis* Fishing Grounds Revealed by Remote Sensing

At the global scale, *S. oualaniensis* exhibits a typical transoceanic distribution pattern across the Indo-Pacific region (Figure 1). In addition to the northwestern Indian Ocean and the South China Sea, the equatorial central-eastern Pacific and subtropical waters also represent important habitats and potential fishing grounds for this species. However, current remote sensing-based investigations of fishing ground formation mechanisms remain largely concentrated in the northwestern Indian Ocean and the South China Sea. To better understand the regulatory mechanisms of fishing grounds under contrasting oceanographic environments, this review focuses on these two representative regions, where substantial differences exist in physical oceanographic processes and ecological regulation mechanisms.

3.1. Spatial Structure of Fishing Grounds in the Northwestern Indian Ocean

The Indian Ocean is one of the most critical marine regions globally for the distribution and fishery exploitation of *S. oualaniensis*. In particular, the distant-water fishing grounds of the Northwest Indian Ocean high seas, centered around the Arabian Sea and its adjacent waters, have become a vital operating area for China's distant-water fisheries [52]. Compared with traditional fisheries statistical methods, the integration of remote sensing and multi-source oceanographic data enables fishing-ground spatial structures to be interpreted within a physical–biological coupling framework, thereby improving the understanding of seasonal habitat dynamics, spatial shifts, and interannual responses of *S. oualaniensis* [15].

Analysis of fishery catch data indicates that the fishing grounds of the purpleback flying squid (*S. oualaniensis*) in the northwestern Indian Ocean exhibit pronounced regional clustering and spatial heterogeneity, with high-CPUE fishing grounds mainly distributed in the relatively higher-latitude waters of the northern part of the study area. Figure 2 illustrates the spatial distribution of fishing ground hotspots for *S. oualaniensis* in the northwestern Indian Ocean. The hotspot analysis revealed clear spatial differentiation

in fishing ground distribution. Significant and highly significant hotspots were mainly concentrated at approximately 15–20° N and 60–65° E, whereas significant coldspots were mainly distributed in the southern part of the study area (approximately 10–15° N). Overall, the fishing grounds exhibited a heterogeneous spatial pattern, with relatively higher CPUE values concentrated in the northern region and lower values generally occurring in the southern part of the study area. However, some fishing grounds can extend toward the vicinity of the Gulf of Aden [37,41,53]. From a temporal perspective, the centers of fishing grounds exhibit latitudinal or longitudinal shifts across months and years, and these migration patterns show strong consistency with seasonal variations in ocean current structures [35,54]. Zhou et al. found that the centroid of *S. oualaniensis* fishing grounds exhibited a northeastward migration trend at the interannual scale [54]. Ma et al. reported that, during 2021–2024, fishing grounds of *S. oualaniensis* in the northwestern Indian Ocean shifted counterclockwise over monthly time scales [24]. Chen et al. further demonstrated that both the interannual variation and seasonal migration patterns of fishing grounds during the main fishing season (September to April of the following year) from 2016 to 2021 followed a northeast–southwest orientation, which was consistent with the direction of the Somali Current [55]. The horizontal migration of *S. oualaniensis* fishing grounds represents an adaptive response to environmental variability, allowing the species to optimize conditions for essential physiological processes, including feeding, thermal regulation, and reproduction.

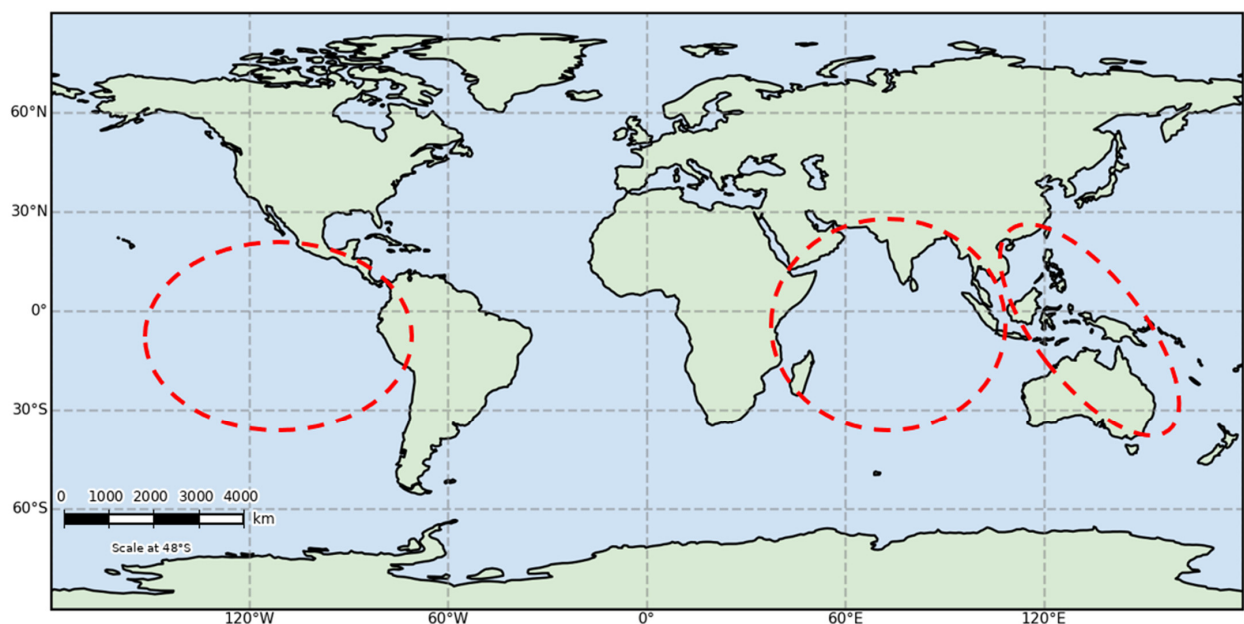


Figure 1. Macro-scale spatial distribution characteristics of *S. oualaniensis*. Note: The red dashed areas represent the three major core habitats and potential exploitation zones for this species globally. Among these, the Northwest Indian Ocean and the South China Sea/Western Pacific are the typical regions where current fishery resource exploitation and mechanistic research are most concentrated.

From an environmental perspective, synthesis of previous studies indicates that the spatial distribution of *S. oualaniensis* in the northwestern Indian Ocean is regulated by the combined effects of sea surface thermal conditions (SST), primary productivity (Chl-a), and oceanographic dynamics. The optimal SST range for *S. oualaniensis* is generally reported to be approximately 26–30 °C. This thermal niche shows clear seasonal variability. In spring and autumn (March–April and October–December), the suitable SST zone (26–29 °C) expands substantially and spatially coincides with high-CPUE fishing grounds [37,55–57]. In contrast, during summer, intensified local upwelling associated with the southwest

monsoon introduces cold deep water and significantly reduces the spatial extent of suitable surface thermal habitats. Nevertheless, SST maintains a stable positive marginal effect on CPUE within the higher temperature range of 28–30 °C [53,58,59]. Regarding primary productivity, Chl-a-enriched regions generated by monsoon-induced upwelling (typically > 0.15–0.20 mg m⁻³) play a critical role in promoting squid aggregation [54]. In particular, frontal zones characterized by strong spatial gradients in SST and Chl-a are frequently associated with high-abundance centers [53]. However, quantitative estimates of optimal environmental thresholds remain uncertain because of differences in sampling domains and model algorithms among studies. For instance, GAM-based approaches usually derive relatively narrow optimal temperature windows [37,41], whereas MaxEnt models often predict comparatively broader habitat suitability ranges [50]. This discrepancy not only reflects methodological differences among models in characterizing ecological response relationships and defining spatial prediction objectives, but also highlights the ecological distinction between “optimal environmental conditions” and “potential suitable ranges” during habitat selection by *S. oualaniensis*. Therefore, future studies should integrate abundance indices, occurrence probabilities, and multi-scale environmental processes to develop integrated ecological niche models that incorporate nonlinear responses and spatial heterogeneity, ultimately providing a more mechanistic understanding of habitat formation processes in *S. oualaniensis*.

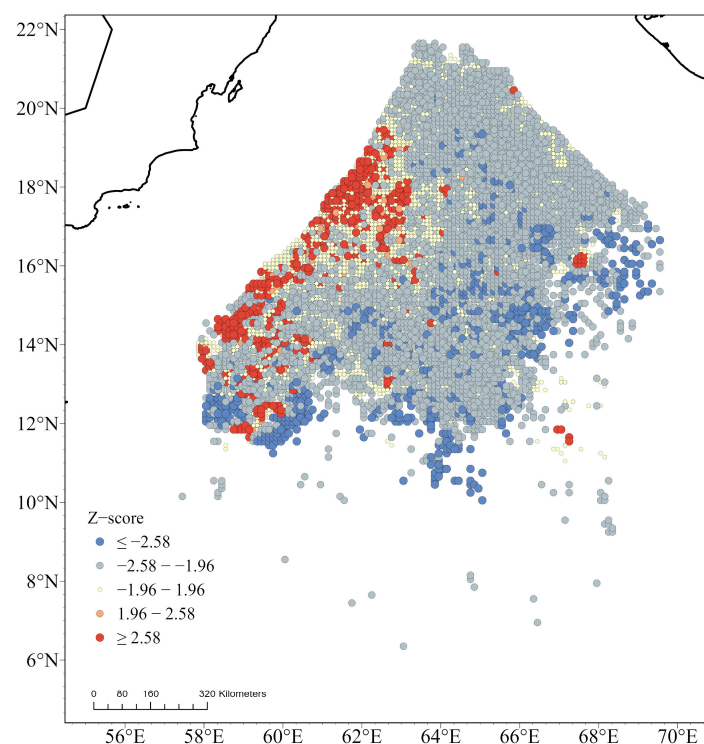


Figure 2. Spatial distribution of hotspots for *S. oualaniensis* fishing grounds in the northwestern Indian Ocean. The data were derived from commercial fishing records collected in the Arabian Sea from 2016 to 2024, covering 55–70° E and 5–23° N and comprising a total of 56,522 fishing-operation records. The original fishing locations were aggregated into a 0.1° × 0.1° spatial grid, and CPUE values were calculated for each grid cell as the input variable. Ordinary kriging in ArcGIS Pro (3.6.0) was applied to construct a continuous spatial surface of CPUE, and the interpolated values were subsequently standardized using Z-scores to classify relative hotspots and coldspots. Z-scores greater than 1.96 and lower than −1.96 indicate relative hotspots and coldspots, respectively, whereas Z-scores greater than 2.58 and lower than −2.58 indicate extreme high-value hotspots and extreme low-value coldspots, respectively. The figure represents the integrated multi-year spatial distribution pattern of *S. oualaniensis* fishing grounds in the study area during 2016–2024.

Regarding horizontal oceanographic dynamics, the distribution and migration of *S. oualaniensis* fishing grounds are strongly influenced by mesoscale processes. High-frequency aggregation areas are commonly associated with low SSH, high EKE, and the margins of cyclonic eddies [15,60,61]; these hydrodynamic features physically manifest as upwelling-induced thermocline shoaling and localized nutrient enrichment. In addition, some high-yield fishing grounds spatially overlap with regions characterized by relatively high EKE values [62,63]. The synchronous migration of resource centers with eddy evolution further indicates that the spatial distribution of *S. oualaniensis* exhibits pronounced responses to ocean dynamic processes [16]. Although previous studies have demonstrated the significant influence of mesoscale eddies on the spatial distribution of *S. oualaniensis*, most existing analyses are based on two-dimensional physical indicators, including SSH, EKE, and eddy type. Consequently, how eddy lifecycle evolution and the three-dimensional ecological structures within eddies regulate the vertical migration and aggregation processes of *S. oualaniensis* remains largely unresolved.

Vertical habitat processes represent another important but understudied aspect. As a diel vertical migrator, *S. oualaniensis* is highly sensitive to vertical thermal and dissolved oxygen structures. A shallower mixed-layer depth (17.8–29.8 m) may favor upper-ocean productivity enrichment, whereas the 20 °C isotherm depth (101.2–134.7 m) constrains the lower boundary of vertical distribution [57]. Against the large-scale habitat background of the widespread mesopelagic Oxygen Minimum Zone (OMZ) in the Arabian Sea, its high-abundance zones are predominantly distributed near the upper boundary of the hypoxic layer and its adjacent waters [64,65]. However, recent studies indicate that such extreme hypoxic constraints are not static, but are rather dynamically modulated by mesoscale physical processes. During the mature stage of cyclonic eddies, the dissolved oxygen concentration at a depth of 150 m (DO150m) is primarily concentrated within the range of 1.2–1.6 mg/L [16]. This redistribution of the biogeochemical environment carves out a “physiological window” for *S. oualaniensis* within the suffocating OMZ background, allowing them to not only avoid lethal deep-layer hypoxia but also precisely harvest abundant food resources (zooplankton biomass: 0.23–0.64 mL/m³) at this depth [35].

At the interannual scale, large-scale climate modes such as ENSO and IOD influence the habitat distribution and fishing-ground dynamics of *S. oualaniensis* by modifying monsoon intensity, ocean circulation, and regional hydrographic conditions. ENSO events can alter habitat extent and location, although the magnitude and direction of responses vary among studies. Some studies found no significant difference in suitable habitat area between spring El Niño and La Niña events but reported a northward shift during El Niño periods [66]. In contrast, other studies showed habitat expansion during La Niña and contraction with northward displacement during El Niño conditions [22]. These discrepancies may be related to differences in study periods, seasonal contexts, and environmental indicators. Nevertheless, ENSO generally regulates habitat redistribution through changes in thermal conditions and productivity. Similarly, positive IOD events enhance habitat suitability and resource abundance in the western Arabian Sea by altering Indian Ocean air–sea interactions [65].

In summary, fishing grounds of *S. oualaniensis* in the northwestern Indian Ocean exhibit distinct characteristics of spatial aggregation, seasonal migration, and vertical stratification. The formation of these multi-scale spatial patterns is not driven by a single environmental factor, but rather represents a complex ecosystem response jointly regulated by surface thermal conditions, primary productivity, mesoscale dynamic processes, and vertically structured biogeochemical environments.

3.2. Spatial Structure of Fishing Grounds in the South China Sea

As a typical semi-enclosed marginal sea ecosystem, the South China Sea is jointly regulated by monsoon systems, Kuroshio intrusion, and complex seabed topography, resulting in spatial structures of fishing grounds that differ markedly from those in the open-ocean environment of the northwestern Indian Ocean.

Previous studies have consistently shown that *S. oualaniensis* fishing grounds in the South China Sea exhibit pronounced patchiness, with high-CPUE areas primarily distributed around the Nansha Islands and their adjacent waters (10–12° N, 112–116° E) [67,68]. This spatial pattern is not random, but is strongly regulated by island–reef topography, shelf–deep ocean transition zones, and local circulation processes. Because the South China Sea is characterized by relatively low background productivity, *S. oualaniensis* aggregation is primarily supported by localized nutrient enrichment associated with physical processes, including topographically induced upwelling and island–reef-generated eddies, which create local productivity hotspots (Chl-a: 0.10–0.35 mg m^{−3}) [21,69]. Consequently, these processes contribute to the formation of a highly heterogeneous and fragmented distribution pattern of squid resources.

Fishing grounds of *S. oualaniensis* in the South China Sea exhibit pronounced seasonal and interannual variability. Previous studies have reported different migration patterns of suitable habitats, with northeastward shifts after summer during 2019–2020 [70]. In contrast, Fan et al. reported that during 2014–2016, the centroid of optimal habitat areas for *S. oualaniensis* in spring shifted southwestward relative to autumn, whereas unsuitable habitat areas migrated northeastward [71]. These differences likely result from variations in temporal scales and environmental backgrounds, reflecting distinct responses to seasonal and interannual environmental changes. At the interannual scale, ENSO influences habitat distribution by modifying SST, monsoon intensity, and regional circulation structures [72]. Previous studies have shown that the potential spawning grounds of *S. oualaniensis* shift northward during La Niña events, while they move southward during El Niño events [6,73–75]. Furthermore, some studies have identified anomalous local conditions during El Niño events, characterized by reduced SST and elevated Chl-a and SSH, indicating that regional oceanographic processes may modulate ENSO-driven changes in resource distribution [72]. In addition, the latitudinal displacement of fishing ground centroids during La Niña events further highlights the role of climate variability in regulating the spatial structure and distribution dynamics of *S. oualaniensis* populations [55].

From the perspective of environmental control mechanisms, SST and Chl-a remain the primary environmental drivers influencing the distribution of *S. oualaniensis* in the South China Sea. However, their effects exhibit pronounced seasonal and regional variations. SST in the South China Sea shows significant seasonal variability, with generally higher temperatures in summer and substantially lower temperatures in winter. Coastal waters are typically cooler than offshore regions, and nearshore SST values in spring and winter are often below 25 °C, forming distinct horizontal thermal gradients (Figure 3; reproduced from Fan et al. [72] under the terms of the CC BY 4.0 license). Previous studies have indicated that the suitable SST range for *S. oualaniensis* is mainly between 24 and 30 °C, with suitable habitats being particularly evident during spring (February–May) [76,77]. However, estimates of the optimal environmental ranges for *S. oualaniensis* vary among studies. Using a MaxEnt model, Fan et al. demonstrated that SST was the key environmental factor regulating seasonal habitat variations in *S. oualaniensis* in the South China Sea [23]. Yan et al. applied a GAM to investigate the relationship between CPUE distribution and environmental factors, and identified suitable conditions of 27–30 °C for SST and 0.10–0.15 mg/m³ for Chl-a concentration [78]. Zhou et al. analyzed fishing production data from light purse seine operations during 2013–2018 and found that suitable environmental ranges for *S.*

oualaniensis included SST values of 25–31 °C and Chl-a concentrations of 0.05–0.27 mg/m³, accompanied by a northward shift in the centroid of fishing grounds [79]. These discrepancies do not necessarily indicate inconsistent environmental preferences, but mainly reflect differences in model structures, data sources, and spatial scales. GAMs emphasize empirical relationships between CPUE and environmental variables, whereas spatial prediction approaches characterize broader habitat patterns. In addition, coarse-resolution datasets may smooth local environmental gradients, affecting estimates of habitat suitability. Future studies should integrate multi-source environmental data and multi-scale models to better resolve the mechanisms driving habitat dynamics of *S. oualaniensis* in the South China Sea.

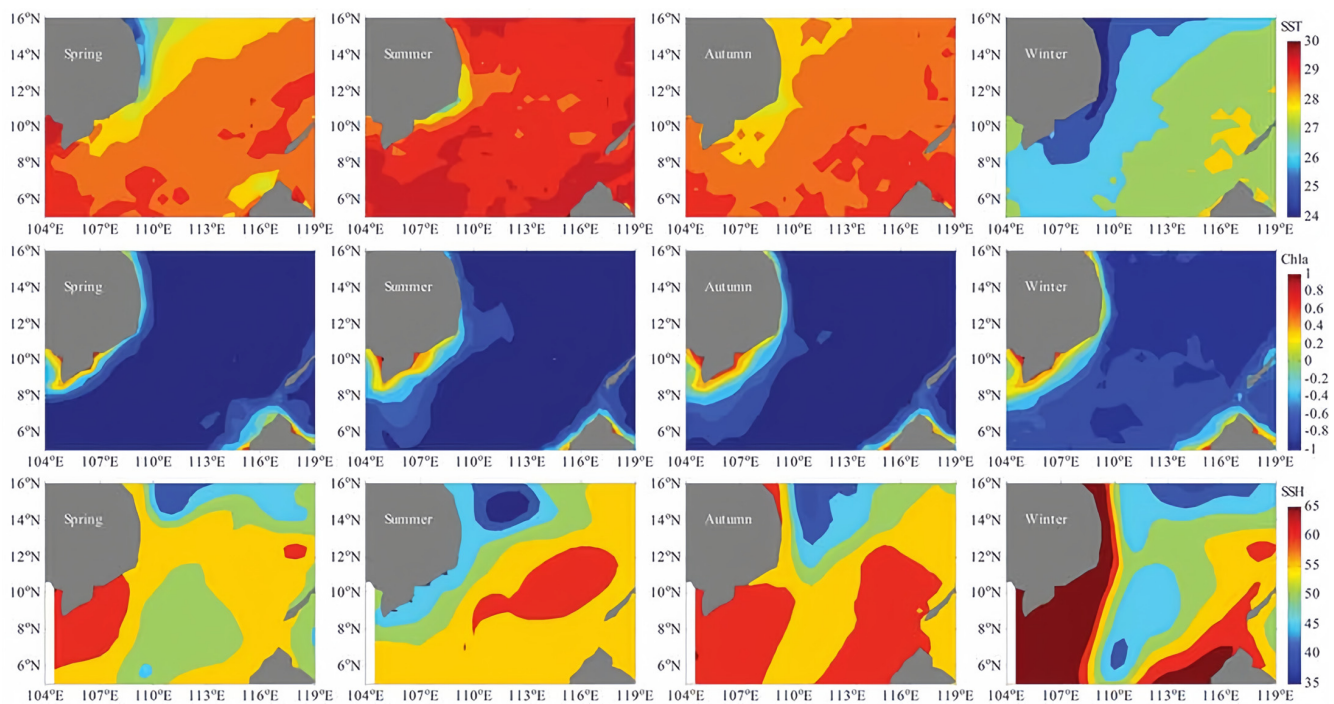


Figure 3. Seasonal spatial distribution of mean SST, Chl-a, and SSH in the *S. oualaniensis* fishing grounds of the South China Sea from 2014 to 2017 (reproduced from Fan et al. [72], licensed under CC BY 4.0.).

Apart from surface environments, vertical structures also constitute key factors influencing *S. oualaniensis* habitats in the South China Sea. Regarding vertical ocean dynamics, the fishing grounds in the South China Sea are primarily influenced by Kuroshio intrusion and its induced mesoscale eddy activities [55,80,81]. These processes modify vertical thermal structures and nutrient distributions, thereby affecting the three-dimensional habitat environment and diel vertical migration (DVM) of *S. oualaniensis* [76]. Cyclonic eddies can induce thermocline shoaling through upwelling, constraining daytime habitat depth while enhancing nighttime surface feeding opportunities [76]. Furthermore, compared to the open ocean, the MLD in the South China Sea exhibits pronounced seasonal variations, which are primarily modulated by the joint effects of monsoon processes and Kuroshio intrusion [82], thereby further modulating the spatiotemporal distribution of *S. oualaniensis* habitats and the migration characteristics of fishing ground gravity centers by altering the upper-ocean thermal structure and nutrient redistribution processes [72]. However, the mechanisms linking vertical physical processes to DVM remain poorly understood and are largely based on qualitative interpretations. Quantitative assessments of how MLD, thermocline gradients, and oxygen conditions regulate vertical migration are still lacking. Future studies should integrate three-dimensional environmental observations and dy-

namic habitat models to better resolve the vertical habitat mechanisms of *S. oualaniensis* in the South China Sea.

3.3. Comparison of Environmental Drivers Between the South China Sea and Northwestern Indian Ocean

A comparison of findings from the two regions suggests that the formation of *S. oualaniensis* fishing grounds in the South China Sea and the northwestern Indian Ocean is governed by both common ecological mechanisms and region-specific environmental processes (Tables 2 and 3). Regarding the response thresholds of key environmental factors, *S. oualaniensis* in both regions displays a high degree of overlap in thermal and productivity boundaries. Specifically, the core SST of high-yield fishing grounds in both sea areas stably falls within a broad thermal range of 25–31 °C. Moreover, they exhibit a significant spatial preference for “moderate-productivity backgrounds (Chl-a concentration of approximately 0.10–0.35 mg/m³)” rather than aligning with extreme chlorophyll-a hotspots. The similarity in environmental suitability ranges between the two regions suggests the presence of shared biophysical mechanisms regulating the distribution of *S. oualaniensis*. As a typical diel vertical migratory species, *S. oualaniensis* in both regions is strongly influenced by the thermocline and mixed-layer structure. Stable vertical thermal stratification provides a fundamental environmental framework that supports its diel shifts in habitat depth [83]; on the other hand, fishing grounds in both regions are preferentially distributed in transitional areas with strong gradients in thermal conditions, nutrient dynamics, and sea surface height anomalies, including oceanic fronts and the peripheries of mesoscale eddies. These dynamic regions facilitate vertical and horizontal water exchange, enhance prey accumulation, and consequently create favorable feeding habitats for *S. oualaniensis* [24].

Table 2. Comparison of suitable environmental ranges associated with *S. oualaniensis* aggregation in the South China Sea and the northwestern Indian Ocean.

Environmental Variable	South China Sea	Northwestern Indian Ocean	Common Characteristics
SST	Approximately 25–31 °C, with optimal conditions mainly concentrated at 27–30 °C	Approximately 25–31 °C, with some studies reporting optimal conditions mainly at 26–29 °C	Both occur within stable suitable thermal ranges
Chl-a	Approximately 0.05–0.35 mg/m ³ , with a relatively suitable range of approximately 0.10–0.15 mg/m ³	Mainly concentrated at ≥0.15–0.20 mg/m ³ , with most suitable conditions occurring above 0.20 mg/m ³	Both exhibit a preference for moderate productivity conditions

Table 3. Comparison of environmental driving mechanisms for *S. oualaniensis* fishing grounds between the Indian Ocean and the South China Sea.

Dimension	Northwestern Indian Ocean Fishing Grounds	South China Sea Fishing Grounds
Core Fishing Grounds	Arabian Sea	Nansha (Spratly) sea area
Spatial Distribution Features	Continuous distribution	Discrete/Reef-associated distribution
Core Driving Forces	Monsoon-driven large-scale upwelling, EKE	Kuroshio intrusion, Island/Reef-induced eddies
Climate Response Modes	Highly sensitive to ENSO and IOD	Influences the Western Pacific Subtropical High (WPSH) and Kuroshio path via ENSO; climate response exhibits indirect and regional characteristics
Formation Mechanism	Upwelling-dynamic dominated	Island/Reef-stratification regulated

Despite the substantial overlap in environmental suitability ranges, the spatial configuration of fishing grounds and the underlying dominant processes differ significantly

between the two regions. The northwestern Indian Ocean is an open ocean basin influenced by monsoon-driven upwelling and basin-scale circulation, resulting in relatively continuous nutrient supply and stronger spatial continuity of fishing grounds. In contrast, the South China Sea is a marginal sea where suitable habitats are strongly affected by island–reef topography, Kuroshio intrusion, and local frontal processes, leading to pronounced patchiness in habitat distribution. Therefore, aggregation of *S. oualaniensis* in the northwestern Indian Ocean is mainly regulated by large-scale oceanographic processes, whereas aggregation in the South China Sea relies more on localized circulation and topographically induced ecological processes.

Regarding climate responses, fishing ground variability in the northwestern Indian Ocean is closely associated with the IOD and ENSO. Climate anomalies mainly influence resource distribution by regulating monsoon intensity and upwelling processes [84,85]. In contrast, fishing grounds in the South China Sea are primarily affected by ENSO-induced variations in monsoon systems, sea surface temperature, and regional circulation structures, exhibiting stronger regional responses [68]. Overall, *S. oualaniensis* in the two regions exhibit similar environmental suitability foundations; however, differences in oceanographic dynamics have shaped distinct fishing ground spatial structures, with the northwestern Indian Ocean showing an open-basin continuous pattern and the South China Sea exhibiting a marginal-sea patchy pattern.

4. Integrated Mechanisms Driving *S. oualaniensis* Fishing Grounds

The formation and spatiotemporal dynamics of *S. oualaniensis* fishing grounds are not determined by a single environmental factor, but rather result from the complex coupling between multi-scale oceanographic physical processes and biological ecological requirements (as shown in Figure 4). To systematically elucidate this process, this section follows a hierarchical framework from micro-scale to macro-scale and from local processes to system-level mechanisms. The comprehensive driving mechanisms of *S. oualaniensis* fishing grounds are examined from four perspectives: local environmental suitability mechanisms, biological–physical coupling processes, regional seasonal regulation mechanisms, and large-scale climate anomaly-driven mechanisms.

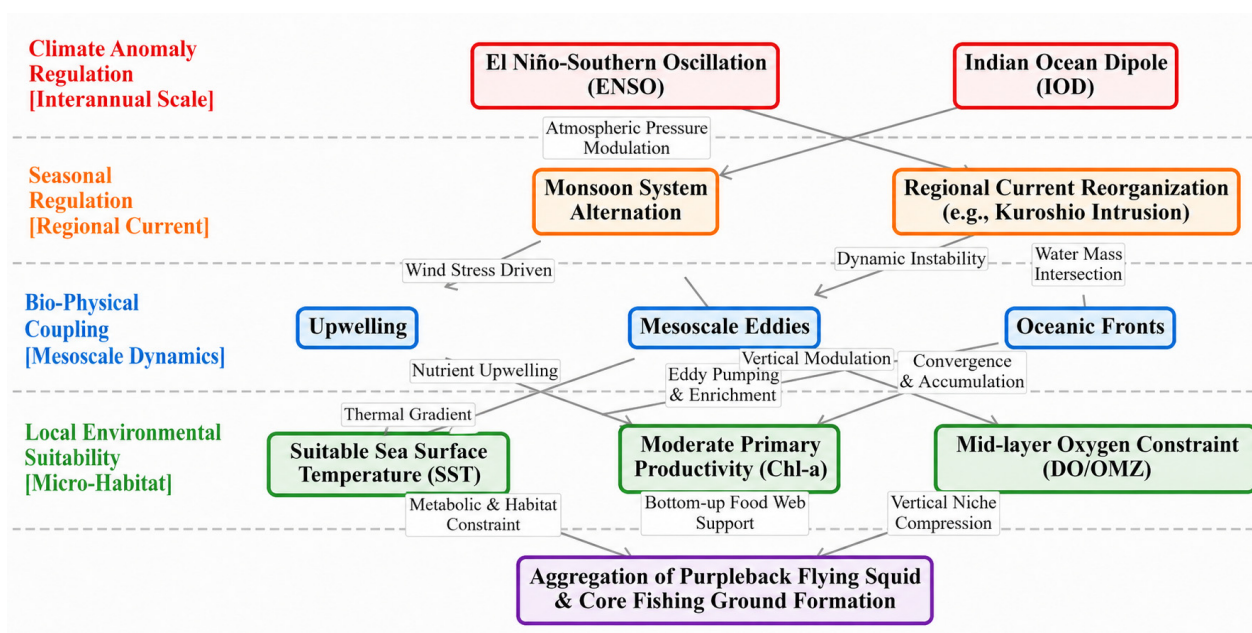


Figure 4. Schematic diagram of the multi-scale cascading driving mechanism for the formation of *S. oualaniensis* fishing grounds.

4.1. Local Environmental Suitability Mechanisms

As an opportunistic cephalopod characterized by a short lifespan and rapid growth, *S. oualaniensis* is highly sensitive to environmental variations, and its fishing ground formation is primarily constrained by local environmental “ecological thresholds.” [21,86,87]. These thresholds are predominantly determined by temperature, DO, and food availability, while also being influenced by environmental factors such as salinity and water mass structures. The core of the local-scale mechanism lies in whether environmental factors fall within optimal ranges, which subsequently dictates whether the resources can establish a stable core zone in a given region.

SST is the most critical limiting factor. Temperature directly regulates the individual energy budget by modulating metabolic rates, feeding efficiency, and growth rates; simultaneously, it indirectly constrains the vertical activity range by influencing the ocean stratification intensity and thermocline depth [37,88]. When the optimal temperature water layer is compressed or shifts upward, the inhabited layer adjusts accordingly, resulting in corresponding changes in spatial distribution [54]. Chl-a concentration and primary productivity constitute the baseline conditions for food supply. Intermediate levels of productivity favor the formation of stable zooplankton and small fish communities, providing a continuous food source for *S. oualaniensis*. Conversely, excessively low or high productivity backgrounds can impair habitat suitability, thereby affecting the intensity of resource aggregation. Salinity and DO serve as vital habitat constraint factors. Salinity regulates habitat stability by affecting water mass structures and density stratification, thereby influencing habitat selection and resource distribution [88]; DO dictates the maximum diving depth and vertical ecological niche width, which can lead to a compression of the vertical activity space, particularly in sea areas where the OMZ is prominently developed.

Consequently, the local environmental suitability mechanism essentially constitutes the “ecological threshold” for fishing ground formation, determining whether the resources can establish a core habitat in a specific region, and serves as the foundational layer within the multi-scale driving framework. While these aforementioned environmental factors directly dictate the habitat suitability for *S. oualaniensis*, the formation of these optimal conditions is further regulated by marine hydrodynamic processes.

4.2. Bio-Physical Coupling Mechanisms

Building upon a suitable environment, the formation of fishing grounds further relies on the regulation of biological productivity by marine hydrodynamic processes. Physical processes, including upwellings, mesoscale eddies, and oceanic fronts, enhance primary productivity by altering water column structures and nutrient transport; this enhancement is subsequently transmitted through the food web, ultimately driving the aggregation of *S. oualaniensis* resources. Upwellings transport nutrient-rich deep water to the surface layer via Ekman pumping or coastal offshore transport, providing the essential nutrient foundation for phytoplankton growth and generating a “bottom-up” energy transfer. As primary productivity signals cascade to higher trophic levels, zooplankton, small fishes, and cephalopod larvae proliferate on a large scale within or along the peripheries of these core productivity zones. Driven by the biological attraction of prey density, *S. oualaniensis*—acting as a top predator—exhibits pronounced spatial resource aggregation, thereby achieving a transformation from physical perturbation to biological resource enrichment.

Mesoscale eddies modulate the transport of nutrients and biogenic particles through mechanisms such as eddy pumping, convergence, and retention effects. Cyclonic eddies facilitate the upward transport of deep nutrients and enhance primary productivity, whereas the peripheries of anticyclonic eddies frequently form aggregation zones for prey organisms. Consequently, high-abundance zones of *S. oualaniensis* are predominantly distributed along

eddy edges or within eddy-front confluence zones [89–92]. Oceanic frontal regions, due to temperature and salinity gradients, create physical barriers and convergence trapping effects that concentrate plankton and small fishes within the frontal zones, thereby forming linear or banded high-abundance bands [93,94].

Different sea areas exhibit variations in their coupling modes; open oceans like the Indian Ocean often present continuous productivity bands dominated by large-scale upwellings [95,96], whereas marginal seas like the South China Sea rely more heavily on mesoscale hydrodynamic processes to sustain localized high productivity [93,97]. Therefore, the bio-physical coupling mechanism dictates the formation, intensity, and spatial configuration of fishing grounds through a “bottom-up” energy transfer process, serving as a vital bridge that transforms local environmental suitability into resource aggregation.

4.3. Seasonal Regulation Mechanisms

On a regional scale, the monsoon system constitutes the dominant controlling factor for the periodic variations in fishing grounds. By regulating large-scale air–sea interactions and sea surface circulation patterns, the monsoon alters upwelling intensity and water column stratification, thereby reshaping the spatial distribution of biological productivity.

In the Northwest Indian Ocean, strong southern winds during summer induce large-scale upwellings along the Arabian Sea and Somali coasts via Ekman pumping. These cold waters carry abundant nutrients up into the euphotic zone, boosting phytoplankton and secondary productivity growth, which provides the production baseline for the subsequent formation of high-abundance fishing grounds [98]. At this time, owing to the intense fluctuations in the sea surface hydrodynamic environment, the peak catch usually lags until the monsoon transition period (September to November), reaching its maximum only after primary productivity has been successfully transferred into secondary biomass. In winter, the reversal of wind direction triggers a reorganization of ocean circulations; the previous upwelling regions transform into downwelling or weakly mixed zones, and the center of gravity of the fishing grounds shifts toward the equator or western areas following the productivity centers, demonstrating a quintessential seasonal displacement [99].

Compared with the Northwest Indian Ocean, the seasonal variations in the South China Sea fishing grounds are influenced by a greater number of localized hydrodynamic processes. Under the influence of the summer monsoon, upwellings, eddies, and frontal activities in the South China Sea intensify, restricting the primary distribution of fishing grounds to the Nansha Islands and their adjacent waters. In winter, alongside adjustments in the circulation architecture and the strengthening of the Kuroshio intrusion, the center of gravity of the fishing grounds undergoes a pronounced migration [72].

In general, the monsoon system shapes the seasonal variation characteristics of *S. oualaniensis* fishing grounds by modulating the marine dynamic environment and productivity regimes. The Northwest Indian Ocean fishing grounds primarily respond to large-scale upwelling processes driven by the monsoon, exhibiting a highly conspicuous seasonal rhythm. Conversely, the South China Sea fishing grounds are simultaneously affected by the monsoon, regional circulations, and mesoscale hydrodynamic processes, culminating in a more complex variation in their spatial positioning.

4.4. Climate Anomaly Regulation Mechanisms

On interannual and longer time scales, large-scale climate modes constitute critical external forcing factors driving fishing ground fluctuations. Superimposed on the seasonal patterns established by the monsoon, large-scale air–sea coupled modes alter wind field structures, sea surface thermal distributions, and marine hydrodynamic processes, thereby modifying productivity levels and the extent of suitable habitats. Climate modes do not

directly act on *S. oualaniensis* resources, but rather alter environmental conditions—such as sea temperature, upwellings, stratification intensity, and primary productivity—thereby influencing the distribution of suitable habitats and the process of resource aggregation.

ENSO and IOD events typically induce anomalous changes in the marine environment, consequently reshaping the spatial configuration of fishing grounds. During El Niño events, certain sea areas frequently exhibit characteristics such as elevated sea surface temperatures, weakened upwellings, and declining productivity, which lead to a contraction of suitable habitats and subsequent shrinkage or spatial shifts in fishing grounds [20]. Conversely, under the influence of La Niña events and certain positive IOD backgrounds, specific research regions display intensified upwelling activities and higher productivity levels, which favor the expansion of suitable habitats and resource aggregation [100]. Furthermore, against the backdrop of long-term climate warming, the continuous rise in sea surface temperatures may trigger a spatial reorganization and a shift in the distributional range of suitable habitats, ultimately impacting regional resource patterns and fishing ground stability.

Different sea areas exhibit variations in their responsiveness to climate anomalies. The Northwest Indian Ocean is simultaneously regulated by both ENSO and IOD, and the impacts of climate anomalies on its upwelling systems and baseline productivity fields are highly direct; consequently, the interannual fluctuations of its fishing grounds are generally pronounced. On the other hand, the South China Sea is primarily affected via the modulation of the monsoon system, regional circulations, and Kuroshio intrusion processes by ENSO, meaning its climate response reflects more regional and indirect environmental variation characteristics [101]. Therefore, by modulating regional environmental backgrounds and marine hydrodynamic processes, the climate anomaly regulation mechanism reshapes the suitable habitat range and resource aggregation patterns of *S. oualaniensis* on an interannual scale, serving as a vital driver for the long-term fluctuations of fishing grounds.

5. Evolution of Remote Sensing-Driven Fishing Ground Prediction Technologies

5.1. Empirical Statistical Analysis Stage

From the late 1990s through the first decade of the 21st century, research on *S. oualaniensis* fishing grounds was generally characterized by the empirical statistical analysis stage. Research during this stage mainly relied on surface ocean remote sensing variables, such as SST and Chl-a. Through correlation analysis, frequency statistics, and empirical regression approaches, these studies investigated the relationships between environmental variables and CPUE, identified suitable environmental ranges for the distribution of *S. oualaniensis* resources, and provided the foundation for the subsequent development of habitat suitability models [56,102]. Among these, the Habitat Suitability Index (HSI) model emerged as the most representative tool of the era [103]. These studies typically constructed HSI models based on suitability functions of environmental factors like SST and Chl-a, performing multi-factor comprehensive evaluations through arithmetic mean, geometric mean, or empirical weighting techniques [104].

In addition to remote sensing environmental data, advancements in resource survey technologies provided crucial support for model construction. The synchronized observation using light falling-nets coupled with scientific echosounders enhanced the capacity to capture the vertical distribution profiles of the resources. By establishing empirical relationships between mantle length and target strength (TS) via acoustic echo analysis, these techniques provided a fundamental basis for estimating resource density [105].

Overall, HSI models have advantages including simple structures, high computational efficiency, and clear ecological interpretations, making them suitable for early-stage resource distribution identification and potential fishing ground delineation. However, these

models rely on empirical thresholds and manually defined suitability functions, which limits their ability to characterize complex nonlinear relationships and interactions among environmental variables. In addition, HSI models mainly focus on surface ocean conditions and provide limited consideration of ecological processes such as thermocline structure, dissolved oxygen variability, and climate-scale environmental changes.

5.2. Multi-Factor Statistical Modeling and Standardization Stage

Entering the second decade of the 21st century, driven by the accumulation of long-term time-series data from satellite products such as MODIS and AVHRR, alongside the systematic organization of fishery production data, research on *S. oualaniensis* fishing grounds gradually transitioned from empirical statistical analysis to a stage characterized by multi-factor statistical modeling and standardization analysis. At the data level, research using remote sensing environmental variables has expanded from single surface parameters such as SST and Chl-a to joint analyses incorporating multiple environmental factors, including SSH, SSHA, and sea surface wind fields [106]. Mohamed et al. incorporated DO, pH, SSS, MLD, and zooplankton biomass to investigate the relationship between *S. oualaniensis* abundance and environmental conditions [57].

At the methodological level, research has gradually evolved from empirical suitability assessment approaches represented by HSI models toward multi-factor statistical modeling methods, including GLMs and GAMs. Compared with HSI models, which rely on empirical weighting schemes and predefined suitability functions, GLMs and GAMs incorporate non-parametric smoothing functions to effectively improve the representation of nonlinear relationships between environmental variables and fishery resources. These approaches achieve a favorable balance between predictive performance and ecological interpretability and have therefore been widely applied in *S. oualaniensis* fishing ground studies [107]. However, these models still rely on assumptions of variable independence and have limited capacity to characterize high-dimensional interactions among multiple environmental variables. Meanwhile, CPUE standardization has become an important research direction during this stage. Studies commonly apply GLM or GAM approaches by incorporating vessel characteristics, fishing operations, temporal factors, and spatial factors as covariates to reduce the influence of differences in fishing effort and improve the reliability of resource abundance index estimates [18]. Concurrently, the HSI model was continuously optimized by integrating methods such as weighted averages, fuzzy logic, and comprehensive indices [108]. In addition, geostatistical methods—including the Standard Deviation Ellipse (SDE), center of gravity (COG) analysis, and hotspot analysis—were extensively utilized to uncover the spatiotemporal migration patterns of fishing grounds [109].

Overall, this stage marked a transition from empirical threshold identification toward the analysis of environmental response mechanisms, thereby improving the statistical interpretability of models. However, GLMs and GAMs still depend heavily on variable selection and predefined model structures, resulting in limited capacity to characterize high-dimensional interactions among environmental variables and complex ecological processes.

5.3. Intelligent Modeling Stage

In recent years, with the rapid development of machine learning and artificial intelligence approaches in the field of fishery remote sensing, as well as the systematic integration of reanalysis products and climate index data, *S. oualaniensis* fishing ground prediction has gradually shifted toward intelligent modeling frameworks. Research datasets have expanded from traditional satellite-derived surface variables to multi-source and multi-scale

environmental information, including SST, Chl-a, SSH, vorticity, MLD, temperature–salinity structures, and climate indices such as ENSO and IOD. This integration enables comprehensive analyses of local environmental variability and large-scale climate processes [64,110].

At the methodological level, machine learning approaches—such as the MaxEnt, Random Forest (RF), Gradient Boosted Trees (GBT), and XGBoost—have been extensively applied to habitat suitability assessment and fishing ground forecasting research [111]. Compared with statistical models like GLM and GAM, these methods do not require pre-specified variable response functions, allowing them to more effectively handle high-dimensional variables, complex nonlinear relationships, and variable interaction effects, while quantifying the contributions of environmental factors through feature importance analysis. Meanwhile, deep learning models, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), have been increasingly introduced into fishing ground prediction studies. These approaches further enhance the capability to characterize spatiotemporal patterns by extracting spatial features from remote sensing data and capturing temporal lag effects in resource distribution. Consequently, they provide new technical pathways for seasonal-scale prediction and short-term forecasting [112].

Overall, this stage represents a transition in research approaches from correlation-based analyses of environmental factors toward multi-scale prediction and climate-driven interpretation. The introduction of machine learning and deep learning models has expanded fishing ground research from local habitat identification to the simulation of resource variability and prediction of long-term trends [34].

5.4. Comprehensive Comparison of Different Prediction Models

Different types of prediction models exhibit distinct differences in predictive performance, ecological interpretability, and application scenarios. Overall, traditional statistical models, such as HSI, GLM, and GAM, have strong advantages in ecological interpretation, whereas machine learning and deep learning models show greater potential in capturing complex nonlinear relationships and improving predictive performance [113].

To provide a more comprehensive comparison of the developmental characteristics of fishing ground prediction approaches across different stages, Table 4 summarizes the representative models and their applications. The HSI model has a simple structure and clear ecological interpretation, making it suitable for potential habitat assessment under limited data availability. However, its predictions rely heavily on empirical thresholds, which limits its ability to reveal complex ecological processes [20]. GLMs are effective for CPUE standardization and evaluating the contributions of environmental variables, with strong statistical inference capabilities. By introducing non-parametric smoothing functions, GAMs further enhance the capability to characterize non-linear response relationships, offering distinct advantages in identifying ecologically suitable ranges; however, both approaches remain constrained by their respective model assumptions [21]. MaxEnt is suitable for potential distribution prediction when only presence data are available [114]. RF and XGBoost can integrate multi-source environmental variables and capture complex interactions among predictors, resulting in high performance in spatial prediction [34]. Deep learning models, such as CNN-LSTM, are particularly suitable for long-term time-series analysis and high-resolution remote sensing data, enabling effective extraction of spatiotemporal patterns in resource distribution. Nevertheless, their interpretability and transferability across different regions require further improvement.

Table 4. Comparison of the development and characteristics of forecasting models for *S. oualaniensis* fishing grounds.

Model	Data Requirements	Nonlinear Representation Capacity	Interpretability	Predictive Capacity	Advantages	Limitations	Applicable Research Objectives
HSI	Low	Low	High	Basic	Simple structure, easy computation, and clear ecological significance; directly constructed based on suitability index curves	Heavy reliance on empirical thresholds; limited capability in describing complex ecological processes	Suitable for preliminary ecological assessment and habitat suitability analysis, particularly during data-limited stages
GLM	Moderate	Low to Moderate	High	Moderate	Strong statistical inference and highly interpretable results; clarifies relationships between environmental variables and CPUE via parametric regression	Strict assumptions on the form of variable relationships; struggles to capture complex non-linearities	Suitable for analyzing the contributions of environmental factors and standardizing resource abundance estimates
GAM	Moderate	Moderate to High	High	Moderate to High	Flexible non-linear fitting using smoothing functions; excels at revealing ecological thresholds and optimal ranges; widely applied	Limited capability to address complex interactions among multiple environmental factors	Suitable for exploring non-linear ecological marginal effects
MaxEnt	Moderate	High	Moderate	High	Requires presence-only data; predicts potential habitats based on the principle of maximum entropy	Sensitive to the selection of background samples; offers limited ecological interpretability	Habitat assessment, potential fishing ground mapping, and spatial prediction of resource distribution
RF	High	High	Moderate	High	Ensemble of multiple decision trees with robust resistance to overfitting; effectively evaluates the relative importance of environmental factors.	Operates as a “black-box” model; lacks straightforward interpretability of underlying ecological mechanisms	Suitable for fishing ground forecasting with multi-variables and high collinearity
XGBoost	High	Very High	Moderate	High	Gradient boosting ensemble with high computational efficiency and predictive accuracy; excellent at processing complex non-linear relationships	Numerous hyperparameters; complex and time-consuming tuning process	Ideal for operational decision-making requiring rapid and frequent iterations
CNN-LSTM	Very High	Very High	Low	High	Integrates CNN for spatial extraction and LSTM for temporal representation; captures joint spatiotemporal features and environmental lag effects	Requires large datasets with high computational costs; possesses weak ecological interpretability and model transferability	Dynamic fishing ground prediction based on large-scale remote sensing time-series data

Therefore, different models should not be regarded as simple alternatives but rather as complementary approaches suitable for different research objectives. Therefore, these diverse models do not simply exhibit a mutually exclusive substitution relationship; rather, they offer highly complementary advantages tailored to distinct research objectives. For scenarios focusing on ecological mechanism interpretation and statistical inference, traditional HSI, GLM, and GAM approaches remain the preferred options. Conversely, for applications prioritizing operational forecasting and high-precision prediction, ensemble machine learning (e.g., RF, XGBoost) and deep learning models (e.g., CNN-LSTM) demonstrate absolute dominance. When fine-scale logbook data are unavailable and only presence-only data can be retrieved, the MaxEnt model serves as an ideal tool for early-stage exploration of new fishing grounds and the reconstruction of potential habitats.

In summary, future research should adopt a dual-track parallel forecasting framework. On the one hand, incorporating Explainable Artificial Intelligence (XAI) is essential to dismantle the “black box” of deep learning, thereby reconciling “high predictive accuracy” with “robust ecological interpretability.” On the other hand, by integrating physical-biogeochemical coupling models, the cross-regional migration and generalization capabilities of these models under climate change scenarios can be enhanced from a three-dimensional dynamical perspective.

6. Limitations and Future Perspectives

6.1. Current Limitations

Overall, although existing studies have systematically explored the formation mechanisms of *S. oualaniensis* fishing grounds from the perspectives of environmental factor identification and statistical modeling, several critical limitations and gaps remain.

(1) Uncertainties in Fishery and Environmental Data

Current research on *S. oualaniensis* fishing grounds relies heavily on commercial fishery logbooks and remote sensing-derived environmental data. Influenced by variations in fishing behaviors, selectivity of fishing grounds, and retrieval errors in remote sensing, both fishery and environmental datasets entail inherent uncertainties. Concurrently, catch data are predominantly derived from actively exploited sea areas, leaving a lack of direct observations regarding resource conditions in unharvested regions, which limits a comprehensive understanding of the full spatial configurations of fishing grounds.

(2) Insufficient Understanding of Three-Dimensional Ecological Processes

Present studies remain dominated by the analysis of two-dimensional sea-surface remote sensing information. Insufficient attention has been paid to three-dimensional ecological processes—such as thermocline structures, DO distributions, mid-layer water mass variations, and the DVM of *S. oualaniensis*—which severely constrains a deeper understanding of fishing ground formation mechanisms.

(3) Need for Deeper Insight into Climate-Scale Driving Mechanisms

Although climate modes such as ENSO and IOD exert critical influences on the resource distribution of *S. oualaniensis*, existing research mostly focuses on the statistical correlations between single climate events and fishing ground variations. The understanding remains inadequate regarding the cascading mechanisms through which climate anomalies regulate resource distributions by modifying marine hydrodynamic processes, biological productivity, and habitat architectures.

(4) Inadequate Interpretability and Generalization Capacity of Predictive Models

Under conditions characterized by strong spatiotemporal heterogeneity of fishing grounds and complex interactions among environmental factors, traditional statistical models exhibit inadequate predictive accuracy and generalization capacity. Consequently, they struggle to capture the high-frequency fluctuation patterns of oceanic species like *S.*

oualaniensis, leaving substantial room for improvement in both model explanatory power and forecasting performance.

6.2. Future Perspectives

To address the aforementioned limitations, future research should focus on the following aspects.

(1) Establishing an integrated three-dimensional autonomous observation and multi-source data fusion system

Future studies should further strengthen the application of autonomous observation systems while improving traditional fishery data and satellite remote sensing observations. This includes the utilization of profiling floats such as Argo/BGC-Argo, autonomous underwater vehicles (AUVs), and marine observation networks to achieve continuous monitoring of three-dimensional ocean environments. Meanwhile, the integration of electronic fishing logbooks, VMS, AIS, and other fishery-related datasets should be enhanced to achieve coordinated observations of fishing activities and marine environmental conditions. Such efforts will facilitate the development of an integrated observation framework combining “satellite remote sensing–in situ observations–autonomous platforms–fishery operations”, providing essential data support for high-precision fishing ground modeling.

(2) Developing physical–biological coupled models for fishing ground formation mechanisms

Future research should move beyond statistical correlation analyses and incorporate physical–biological coupled models to interpret fishing ground formation mechanisms from the perspective of interactions between oceanographic dynamics and ecological processes. Key research directions include investigating how physical processes, such as upwelling, mesoscale eddies, and frontal systems, regulate nutrient transport and primary productivity, as well as their cascading effects on planktonic ecosystems and cephalopod aggregation. Furthermore, ocean circulation models (e.g., ROMS and HYCOM) combined with ecological models (e.g., NPZ models) could be integrated to establish process-based predictive frameworks linking physical forcing to biological responses, thereby improving the mechanistic understanding of *S. oualaniensis* fishing ground formation.

(3) Advancing Multi-Source Remote Sensing Fusion and Intelligent Forecasting Technologies

With the rapid advancement of artificial intelligence-based remote sensing inversion, high-resolution ocean satellites, Ocean LiDAR (Light Detection and Ranging), and satellite constellation observations, the acquisition of more refined and continuous marine environmental information is on the horizon. Building upon these breakthroughs, future research should further fuse remote sensing data, reanalysis products, climate indices, and fishery production data to develop advanced machine learning, deep learning, and multi-model ensemble forecasting methods, thereby enhancing the capacities for fishing ground identification, resource assessment, and dynamic forecasting. Concurrently, intensifying research on model interpretability is paramount to achieving a synergistic improvement in both predictive accuracy and ecological mechanism interpretation.

(4) Developing multi-source remote sensing integration and intelligent prediction technologies

With the advancement of artificial intelligence-based remote sensing inversion, high-resolution ocean satellite observations, Ocean LiDAR, and satellite constellation observation technologies, future studies are expected to obtain more detailed and continuous information on marine environmental conditions. On this basis, remote sensing data, reanalysis products, climate indices, and fishery production data should be further integrated to develop machine learning, deep learning, and multi-model ensemble prediction approaches, thereby improving capabilities in fishing ground identification, resource assessment, and

dynamic forecasting. Future research should incorporate XAI methods, such as Shapley Additive Explanations (SHAP) analysis, the Local Interpretable Model-Mgnostic Explanations (LIME) approach, and attention mechanism visualization. These methods can enhance predictive performance while simultaneously revealing the pathways and contribution mechanisms of key environmental variables, ultimately achieving a balance between high-accuracy prediction and ecological mechanism interpretation.

(5) Strengthening Research on Resource Responses Under Global Climate Change

Against the backdrop of global climate change, the impacts of large-scale climate processes—such as ENSO, IOD, and ocean warming—on the resource distribution and fishing ground patterns of *S. oualaniensis* are likely to intensify further. Future endeavors should strengthen the investigation into the coupling mechanisms between climate anomaly events and resource fluctuations, revealing the long-term impacts of climate change on habitat structures, resource abundance, and fishing ground stability. This will provide a robust scientific foundation for the sustainable utilization and fishery management of *S. oualaniensis* resources.

Author Contributions: Conceptualization, W.F. and R.Z.; literature search, W.F., R.Z. and X.C.; literature screening and organization, W.F. and X.C.; data analysis and interpretation, W.F., R.Z. and Y.S.; visualization, Y.S.; writing—original draft preparation, W.F. and R.Z.; writing—review and editing, R.Z., Y.W., G.Z. and F.T.; supervision, F.T.; project administration, F.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Program on the Survey of Pelagic Fishery Resources and the Program on the Survey, Monitoring and Assessment of Global Fishery Resources (Comprehensive Scientific Survey of Fisheries Resources at the High Seas), both sponsored by the Ministry of Agriculture and Rural Affairs.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the article, and further inquiries can be directed to the corresponding authors.

Acknowledgments: The authors would like to thank all members of the research group for their valuable discussions and support during the preparation of this review.

Conflicts of Interest: The authors declare no conflicts of interest.

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