ISSN 2616-5872 Vol.6, Issue 4: 95-99, DOI: 10.25236/AJEE.2024.060414

Selection of Marine Environmental Factors in Oceanic Fishery Forecasting and Advances in Fishery Forecasting Models

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Abstract: *The marine environment is the most critical factor affecting the formation of fishing grounds. It is very important to explore how the marine environment affects the formation of fishing grounds. In recent years, more and more people have begun to pay attention to the relationship between various marine environmental factors and the formation of fishing grounds, which has led to the rapid development of fishing ground prediction and has formed a certain industry scale, which has provided some help for the scientific development of Fisheries in China. This paper summarizes the relationship between several marine environmental factors such as chlorophyll a (Chl-a), sea surface height (SSH), sea surface salinity (SSS) and sea surface temperature (SST) and the formation of fishing grounds, and briefly summarizes the models used by people to predict fishing grounds in recent years, reviews the research results of researchers at home and abroad in the past, and puts forward some suggestions for the future research and development.*

Keywords: *marine environmental factors; fishing ground forecasting; machine learning*

1. Introduction

Human development has long depended on the ocean, making the sustainable development and utilization of marine natural resources, as well as the promotion of green economy and marine ecological protection, increasingly important. It is evident that in the foreseeable future, countries will place greater emphasis on the sustainable development of fisheries science. In recent years, the serious decline of major economic fish species in coastal areas and the increasing costs of distant water fishing have posed severe challenges to the fishing industry. Particularly in the past decade, rising fuel costs have significantly impacted fishing efficiency, exerting tremendous pressure on fishermen and fishing enterprises. Therefore, studying the distribution of fishing grounds and analyzing the factors contributing to their formation can provide valuable references for locating fishing grounds and developing fisheries scientifically.

The distribution of fish in the ocean is influenced by both the biological characteristics of the fish and external environmental factors. Hence, the formation of fishing grounds is closely related to the marine environment and the ecology of fish schools. The marine environment is essential for the survival and activities of fish schools. Any change in environmental factors in the ocean can lead to shifts in the location and scale of fishing grounds. Since the modern era, humans have recorded various environmental factors in the ocean and used different methods to establish statistical models for forecasting fishing grounds, achieving certain results. This paper summarizes the environmental factors observed for fishing ground forecasts and their causes and reviews several common fishing ground forecasting models to provide references for future research.

2. Environmental Factors

Common environmental factors used for fishery forecasting generally include Sea Surface Temperature (SST), Sea Surface Height (SSH), Sea Surface Salinity (SSS), Chlorophyll a (Chl-a), eddy kinetic energy, atmospheric pressure, and the carbon cycle. This paper selects the environmental factors currently commonly used for fishery forecasting both domestically and internationally. For example, it considers various fishery forecast analyses involving sea surface temperature, analyses of changes in fishery distribution caused by water mass kinetic energy, the impact of sea surface height and anomalies on fishery distribution, studies on the relationship between sea surface salinity and fishery formation, and the role of Chlorophyll a in fishery formation. Additionally, it summarizes the application research of some less commonly used marine environmental factors for fishery forecasting, such as the changes in temperature and salinity elements in the vertical structure and the alteration of dissolved oxygen content. Many oceanic fish do not remain in a single water layer; for instance, tuna, a highly migratory oceanic species, generally operate in different water layers (0-300 m) in various geographic ranges. Compared to surface water temperature, tuna distribution may be more closely related to subsurface water temperature, and as water depth increases, the thermocline may also affect tuna distribution. Furthermore, related studies have shown that the vertical structure of the marine environment has a certain impact on fish schools.

2.1 Sea Surface Temperature

Sea Surface Temperature (SST) is one of the crucial environmental conditions affecting the survival of marine fish. SST influences not only the living environment of fish but also the availability of various fish species' food, ocean currents, and nutrient conditions. In recent years, greenhouse gas emissions have raised sea surface temperatures, altering the habitats of large algae and fish in the ocean. Chen Xinjun et al. [1] analyzed the production data of tuna purse seine fishing in the central-western Pacific from January 1990 to July 2001, along with corresponding monthly average SST anomalies. They found that during normal years, the main fishing grounds were distributed between 16°N-12°S, 136°-152°E; during El Niño years, the fishing grounds expanded to 134°-155°E; during strong El Niño years, the fishing grounds were located between 14°N-14°S, 131°-153°E; and during La Niña years, the fishing grounds were distributed between 14°N-14°S, 131°-153°E. This indicates that changes in SST due to climatic conditions do affect the central fishing grounds of tuna.

Frequent interactions between different water masses in the ocean form boundary zones of varying spatial scales. Oceanic fronts are boundaries created by different water masses, influenced by advection, monsoons, and topography. These fronts significantly impact the distribution of biological resources and primary productivity in the ocean. Temperature fronts are areas where warm and cold water masses converge, leading to high productivity due to water agitation. Therefore, studying the impact of environmental factor fronts on fishing grounds is essential. Nieblas et al. [2] confirmed this through their research on bluefin tuna spawning grounds in the southeastern Indian Ocean, finding that bluefin tuna prefer spawning in areas with active temperature fronts.

2.2 Sea Surface Height

Sea Surface Height (SSH) may not have as direct an impact on fish activity as temperature, but it is a key factor influencing fish migration, aggregation, and distribution [3]. SSH is closely related to temperature and salinity and contains information about ocean currents, tides, water masses, and mesoscale eddies, which play a unique role in fisheries analysis. With the launch of ocean environment dynamic satellites, analyzing the relationship between SSH and fishing grounds has become more convenient. Data on SSH anomalies and geostrophic currents extracted from satellite altimeters can accurately indicate ocean water mass movements or eddies, which often induce vertical water movement, enhancing nutrient mixing and increasing phytoplankton, ultimately leading to an increase in fish populations that feed on plankton.

There are two main applications of SSH data in predicting fishing grounds: using SSH directly to analyze ocean current conditions and the relationship between warm and cold water masses and temperature fronts, or using SSH anomalies for fishing ground predictions. Using SSH as an environmental factor directly affecting fish survival ensures a certain degree of accuracy, as SSH results from the combined effects of water masses, ocean currents, temperature, salinity, and upwelling.

2.3 Sea Surface Salinity

Salinity affects the distribution of fish and other aquatic economic animals, making it a significant factor in determining the location of fishing grounds. Suitable water temperature and salinity are conducive to the formation of spawning grounds. Mixed water areas where high salinity offshore water meets low salinity coastal water, cold and warm currents converge, and upwelling occurs can also form excellent fishing grounds. These areas typically have abundant nutrients, leading to high primary productivity and attracting large fish populations[4].

2.4 Chlorophyll a Concentration

Chlorophyll a concentration can indicate the primary productivity of a sea area, influencing the biomass of organisms and, consequently, the abundance of zooplankton that feed on them, affecting mid-upper layer fish populations. For instance, Sagarminaga et al. [5] found that longfin tuna catches in the northeastern Atlantic are generally distributed in areas with frequent chlorophyll a fronts. Wang Yanfeng et al. [6] determined that fishing grounds for light trap nets in the Beibu Gulf are concentrated in areas with chlorophyll a concentrations of 0.5-1.5 mg/m³.

2.5 Other Oceanic Environmental Factors

Besides the commonly used environmental factors mentioned above, other factors can also be considered in fishing ground forecasts. For example, Van Jiangtao et al. [7] considered vertical temperature structure for forecasting mackerel fishing grounds, finding a close relationship between fishing ground location and temperature gradient, varying with seasons. Perry et al. [8] used vertical temperature and salinity factors to predict the distribution of demersal fish (such as flounder and cod), concluding that their distribution correlates with these factors. Other factors like dissolved oxygen and sea surface wind speed also influence fish aggregation. Dissolved oxygen is essential for fish survival, especially for fast-swimming species like tuna, while sea surface wind speed affects water layer mixing and fish aggregation. Ocean currents also play a significant role in fish aggregation, with major economic fish species often found in areas with intense ocean current interactions.

3. Progress in Fishing Ground Forecast Models

Currently, fishery forecasting generally refers to spatial forecasting of fishing grounds, predicting the location of fisheries or the spatial distribution status of fish resources. Both domestic and international forecasting models primarily focus on spatial forecasting models for fisheries. In recent years, marine remote sensing has provided extensive real-time ocean environmental data, geographic information system (GIS) technology has offered spatial analysis and visualization capabilities for fishing grounds, and artificial intelligence (AI) technology has introduced new directions for fishery forecasting, enhancing its precision. Fishery forecasting models are generally categorized into three major types: statistical models, machine learning and AI models, and mechanistic/process-based models. Statistical models typically include linear regression models, Bayesian models, time series analysis, and spatial overlay analysis methods. In machine learning, models such as BP neural networks, support vector machines, and random forests are commonly used for fishery forecasting. Deep learning, as a rising technology, employs convolutional neural networks (CNNs) which can enhance model expression capabilities by dimensionality reduction and complexity reduction through convolution, effectively suppressing overfitting. Pooling layers and nonlinear activation functions enhance resistance to noise and deformation, improving generalization performance. By increasing the depth and width of convolutional and fully connected layers, CNNs adapt to complex tasks. Currently, this method shows promising results in classifying high and low yield areas within fishing zones. Regarding the construction of model datasets using marine environmental factors, both single-factor and multi-factor fishery forecasting models are utilized.

3.1 Statistical Models

Early fishing ground forecast models were predominantly statistical, employing methods such as linear regression models, Bayesian models, time series analysis, and spatial overlay analysis.

Linear regression models require ample data, which is then organized and analyzed to compute functional relationships between various factors, subsequently using these functions to predict fishing ground formation. However, due to the dynamic nature of fishing grounds and the limitations of basic assumptions, traditional statistical methods struggle with non-linear and complex spatial data. Consequently, simple linear regression has fallen out of favor, with more complex polynomial and exponential regression models being preferred.

Bayesian models calculate the frequency of fishing grounds appearing under certain environmental conditions and the corresponding conditional probabilities and prior probabilities. Using Bayesian theory, the posterior probability is then computed to determine the likelihood of fishing ground formation. However, the assumption of independence between factors in Bayesian methods is often unrealistic for environmental conditions affecting fishing grounds. Constructing Bayesian networks might mitigate this issue.

Time series analysis involves numerical analysis with temporal sequence characteristics, crucial for predicting the dynamics of fishery resources and guiding scientific fishing efforts. However, time series analysis requires stationary random sequences, whereas fishery resource fluctuations are non-stationary. Thus, sequence processing techniques, such as using grey system theory to analyze deterministic trends in fishery resource sequences, are necessary.

Spatial overlay analysis employs visualization techniques to analyze the historical spatiotemporal distribution of fish, combining biological characteristics with remote sensing environmental data to reveal the dynamic intersections of fishing grounds and oceanic environmental elements. This approach effectively observes fishing ground changes in fluctuating ocean environments.

Some researchers use geostatistical interpolation methods for fisheries data. While geostatistics shares some similarities with classical statistics, it considers the spatial and regional structure when selecting variables, leading to potential correlations among variables. Moreover, geostatistics typically addresses spatial statics, which can limit its application in fishing ground forecasts.

3.2 Machine Learning Methods

With the development of machine learning, more researchers are employing related models for fishing ground forecasts, such as BP neural networks (Back Propagation, BP), convolutional neural networks (CNN), random forests (RF), and support vector machines (SVM).

BP neural networks possess strong non-linear mapping capabilities and, with sufficient neurons in the hidden layers (typically three or more layers), can approximate real values closely. Thus, BP neural networks are suitable for predicting the distribution of fishing grounds using extensive oceanic environmental data or spatiotemporal distributions. However, BP neural networks face challenges like slow learning speed, susceptibility to local minima, and the absence of clear guidance on neuron count, all of which require further improvement.

Deep learning models, particularly convolutional neural networks (CNNs), have shown excellent predictive results with high-dimensional and large datasets, automating feature engineering and minimizing human influence. CNNs can perform supervised and unsupervised learning, leveraging linear algebra principles to automatically select advantageous features from images. CNN-extracted high-resolution remote sensing features have effectively forecasted dynamic ocean environments' fishing grounds. For instance, Zhang Tianjiao et al. [9] incorporated a convolutional autoencoder into a deep embedded clustering network to forecast bigeye tuna in the southwestern Indian Ocean, enhancing prediction accuracy by preserving data's local features.

Support vector machines (SVMs), designed for binary classification problems through supervised learning, perform well with smaller datasets and have seen some application in fishing ground forecasts, yielding satisfactory results. For example, Chen Hao [10] used SVM to predict tuna fishing grounds in the Cook Islands, finding it highly effective for central fishing ground predictions. However, SVMs face challenges with large datasets, such as slow processing speeds and extensive computational demands, and lack structured optimal parameter selection methods, necessitating future improvements.

4. Conclusion and Outlook

In summary, the four discussed oceanic environmental factors—SST, SSH, SSS, and Chl-a—each significantly influence the formation of fishing grounds. SST, SSH, and SSS have notable correlations with fishing ground formation, while Chl-a's relationship may be less pronounced due to factors like ocean currents or extensive spatial distribution. Nonetheless, Chl-a holds statistical significance as an indicator of primary ocean productivity. Although this paper focuses on SST, SSH, SSS, and Chl-a, numerous other environmental factors, such as wind direction, tidal-driven fronts, eddy kinetic energy, and the Kuroshio Current, also impact fishing ground formation.

Currently, a common approach is to consider various environmental factors as habitat indices and combine them into comprehensive habitat indices for fishing ground forecasts. This method accounts for the weight of each factor's influence, resulting in more accurate predictions. Traditional statistical methods for fishing ground forecasts are increasingly replaced by more complex models, and more researchers are adopting machine learning methods, achieving certain successes. Ensemble learning

ISSN 2616-5872 Vol.6, Issue 4: 95-99, DOI: 10.25236/AJEE.2024.060414

methods have shown better performance than traditional single-model forecasts, though overall prediction accuracy still needs improvement. Each machine learning model has inherent deficiencies, requiring optimization for better results.

The distribution of fish species in the ocean is vast and variable, with significant differences between species. Accurate understanding of fishing ground causes and precise forecasts require consideration of not only environmental factors but also the life history, population status, and survival mechanisms of various fish species. Additionally, the spatial distribution, timing, sampling projects, and data resampling of oceanic environmental factors need to be standardized to ensure data validity and usability. Current predictions and validations of fishing ground formations often rely on readily available large datasets, potentially overlooking harder-to-obtain but relevant environmental factors. Future research should consider fishing ground formation within the broader context of physical oceanography, fisheries oceanography, and ecological dynamics to establish more accurate relationship models and achieve precise fishing ground forecasts.

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