Advances in Computer and Communication, 2025, 6(1), 6-13
https://www.hillpublisher.com/journals/acc/
ISSN Online: 2767-2875

Study on Computer Fuzzy Comprehensive Evaluation and Correlation Analysis—Taking the Study on the Best Habitat of Antarctic Krill as an Example

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How to cite this paper: Chenyu Pu. (2025) Study on Computer Fuzzy Comprehensive Evaluation and Correlation Analysis—Taking the Study on the Best Habitat of Antarctic Krill as an Example. *Advances in Computer and Communication*, 6(1), 6-13.
DOI: 10.26855/acc.2025.01.002

Received: December 29, 2024
Accepted: January 27, 2025
Published: February 25, 2025

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Abstract

Antarctic krill (Euphausia superba) plays a vital role in the Southern Ocean ecosystem, serving as a key link between primary producers and higher trophic levels. This study investigates the correlation between Antarctic krill density and environmental variables, including sea surface temperature, chlorophyll concentration, and mixed layer depth, using Pearson's correlation coefficient and fuzzy entropy analysis. Data from the KRILLBASE and GLORYS2v4 databases were analyzed, focusing on the period from 2010 to 2016. Results reveal that sea bottom temperature and mixed layer depth significantly influence krill distribution, while nutrient-related variables indirectly affect abundance. Fuzzy entropy identified 195.0 meters as the optimal depth for krill habitat, characterized by stable environmental conditions. These findings provide insights into krill ecology and support sustainable management of Antarctic marine resources.

Keywords

Correlation Analysis; Fuzzy Entropy Evaluation; Antarctic Krill; Euphausia Superba

1. Introduction

Antarctic krill (scientific name: Euphausia superba), commonly referred to as the Antarctic krill, is a gregarious marine crustacean that can form large swarms [1], sometimes reaching densities of 10,000–30,000 individuals per cubic meter [2]. Due to its enormous biomass, Antarctic krill serves as a crucial food source for many important species, such as whales, seals, and seabirds. Thus, they play a pivotal role in the Antarctic marine ecosystem as a key link between primary producers and higher-level consumers [3]. In addition to their ecological significance, Antarctic krill are widely utilized in aquaculture, nutritional supplements, and biopharmaceuticals, highlighting their substantial economic value [4].

In recent years, an increasing number of scholars have conducted research on Antarctic krill [5-10]. Numerous studies have shown that environmental factors influence the ecological characteristics of species, such as growth, reproduction, and distribution, thereby affecting fishing efficiency. Multiple studies have demonstrated a close relationship between Antarctic krill distribution and various environmental factors. For example, some research indicates that the regional abundance of krill in the South Atlantic during summer is positively correlated with the extent of sea ice from the previous winter [5, 6]. Among various phytoplankton, diatoms are considered a significant food source for krill, and chlorophyll-a concentration can be used to assess the food environment [7, 8]. Other studies suggest that changes in krill abundance in certain regions around the Antarctic continent are associated with ocean circulation [9, 10].

The impact of different environmental factors on Antarctic krill varies significantly. Existing research has predominantly focused on the analysis of a single or a few environmental factors, lacking systematic studies on the combined effects of multiple factors. Although current studies generally explore the relationship between Antarctic krill and environmental factors, there are differences in research methods and data processing. Traditional statistical models, such as Generalized Linear Models [11] (GLM) and Artificial Neural Networks [12] (ANN), are commonly used. In this study, Pearson's correlation coefficient is employed to calculate the correlation between environmental factors and Antarctic krill distribution. Additionally, the fuzzy entropy evaluation method is applied to discuss the suitable living conditions for Antarctic krill from the vertical (water depth) perspective.

2. Materials and Methods

2.1 Study Area

Antarctic krill area species of krill that live in the Antarctic waters of the Southern Ice Ocean, and fishing operations are mainly in the South Atlantic region. Figure 1 shows a map of the main fishing areas in the Antarctic region from the Commission for the Conservation of Antarctic Marine Living Resources website. The fishing areas are divided into three main Fishing Areas (FA) 48, 58, and 88, and each main fishing area is divided into several subareas.

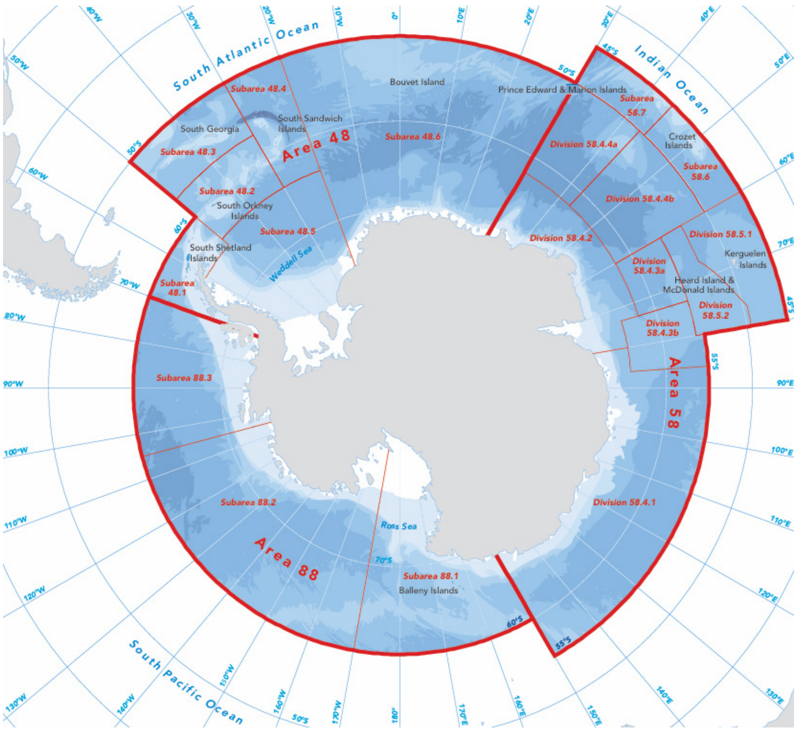

Figure 1. CCAMLR Antarctic fishing zone division map [13].

2.2 Data

2.2.1 Krill Data

The Antarctic krill density distribution data were obtained from the Southern Ocean Antarctic Krill Database (KRILLBASE), covering the period from 1926 to 2016 [14]. The krill data samples were compiled from survey projects conducted by 10 countries, including the United States, the United Kingdom, and Norway, during the period from 1926 to 2016. The data fields include measurement dates, trawling duration, geographical coordinates (latitude and longitude), water temperature, krill swarm depth, and krill density. Due to significant environmental changes in the Antarctic region since 1926, this study focuses specifically on the period from 2010 to 2016. After data screening and statistical processing, the distribution points of Antarctic krill were obtained, as shown in Figure 2.

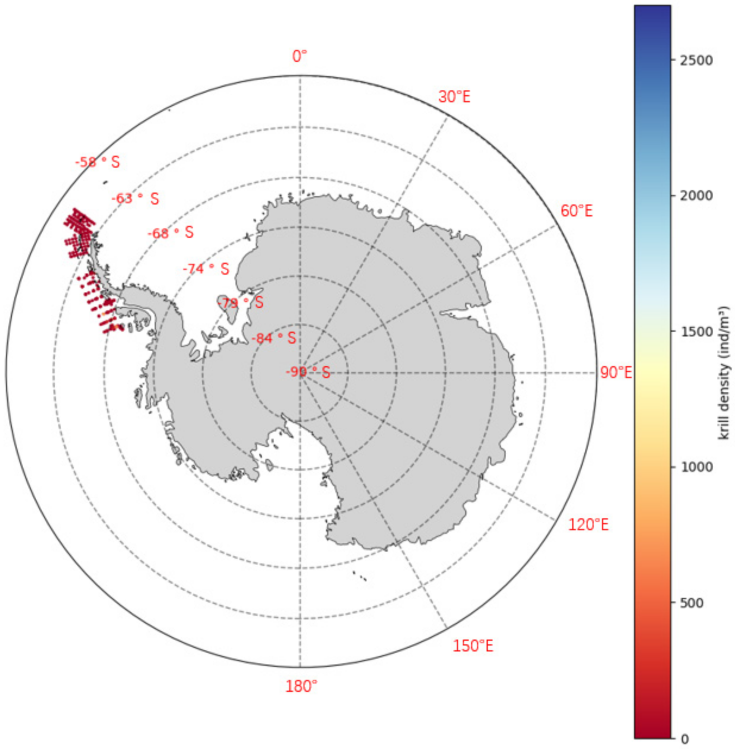

Figure 2. KRILLBASE Antarctic krill distribution point.

2.2.2 Environmental Data

The marine environmental variables were obtained from the Global Ocean Reanalysis Simulation (GLORYS2v4), which includes 9 physical variables and 6 ecological variables. Table 1 presents the definitions, abbreviations, and units of all 15 variables. The physical variables primarily represent abiotic environmental factors, such as ocean hydrodynamics and related environmental parameters [15], while the ecological variables include biologically relevant factors, such as phytoplankton [16]. Among these, the sea ice duration index represents the proportion of time each grid cell is covered by sea ice. The environmental variables were preprocessed using MATLAB software and filtered based on three constraints—latitude, longitude, and time—from the KRILLBASE dataset to ensure compatibility for further research and analysis.

Table 1. Physical and atmospheric variables from GLORVS2v4

Physical variables	Description	unit	Ecological variables	Description	unit
mlotst	Mixed Layer Depth	m	chl	Chlorophyll concentration	$mg.m^{-3}$
zos	Sea surface height	m	no3	Nitrate concentration	$mmol/m^3$
bottomT	Sea bottom temperature	℃	si	Silicate concentration	$mmol/m^3$
sithick	Sea ice thickness	m	o2	Dissolved oxygen	$mmol/m^3$
siconc	Ice concentration	1	nppv	Net primary production	$mg.m^{-3}.day^{-1}$
thetao	Potential temperature	℃	po4	Phosphate concentration	$mmol/m^3$
so	Salinity	psu			
uo	Eastward ocean current velocity	m/s			
vo	Northward ocean current velocity	m/s			

2.3 Methods

2.3.1 Data Preprocessing

Before conducting the correlation analysis, the raw environmental data and Antarctic krill density data were preprocessed to ensure data quality and consistency. The preprocessing steps included environmental data interpolation, outlier removal, and data normalization.

(1) Environmental data interpolation

Due to the irregular sampling intervals and potential missing values in the environmental data, linear interpolation was applied to estimate the values at unsampled depths [17]. Linear interpolation was chosen for its simplicity and effectiveness in filling gaps in continuous data [18]. For each environmental parameter (e.g., temperature, salinity, chlorophyll concentration), the missing values at a given depth were estimated based on the nearest available data points above and below that depth. This approach ensured that the environmental data were continuous and suitable for subsequent analysis [19].

(2) Data outlier removal

To eliminate the influence of outliers in the dataset, the z-score method was employed [20]. The z-score for each data point was calculated as follows:

$$z = \frac{x - \mu}{\sigma}$$

where x is the observed value, μ is the mean of the data, and σ is the standard deviation. Data points with an absolute z-score greater than 3 were considered outliers and removed from the dataset. This threshold was chosen based on the assumption that the data follow a normal distribution [21], and values beyond three standard deviations from the mean are statistically rare and likely to be anomalies.

(3) Data normalization

To ensure that all environmental variables were on a comparable scale, the data were normalized using the min-max normalization method [22]. This technique rescales the data to a fixed range, typically [0, 1], using the following formula:

$$x_{normalized} = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})}$$

where x is the original value, $x_{\min}$ is the minimum value of the dataset, and $x_{\max}$ is the maximum value. Min-max normalization was chosen because it preserves the relationships between the original data values and is particularly useful when the data are to be used in algorithms, which are sensitive to the scale of the input variables.

2.3.2 Correlation Analysis

To investigate the relationship between Antarctic krill density and environmental variables at different depths, Pearson's correlation coefficient was employed [23]. Pearson's correlation coefficient measures the linear relationship between two continuous variables, ranging from -1 to 1, where 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no correlation. The formula for Pearson's correlation coefficient r between two variables X and Y is given by:

$$r = \frac{\sum_{i=1}^{n}(X_i - X)(Y_i - Y)}{\sqrt{\sum_{i=1}^{n}(Xi - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

where X_i and Y_i are the individual data points, $\overline{X}$ and $\overline{Y}$ are the means of X and Y, respectively, and n is the number of data points. In this study, Pearson's correlation coefficient was calculated between Antarctic krill density and each environmental variable at different depth layers. The significance of the correlation was tested using a p-value threshold of 0.05.

2.3.3 Fuzzy Entropy Evaluation

Fuzzy entropy was employed to evaluate the complexity and uncertainty of the Antarctic krill density distribution in relation to environmental variables. Fuzzy entropy is a measure of the unpredictability or irregularity of a time series or spatial dataset, where higher entropy values indicate greater complexity [24]. The calculation of fuzzy entropy involves the following steps:

(1) Constructing the Fuzzy Membership Function: A fuzzy membership function is defined to quantify the degree to which a data point belongs to a specific set. In this study, a Gaussian membership function was used due to its smoothness and adaptability.

(2) Calculating the Similarity Degree: For a given time series or spatial dataset $X = \{x_1, x_2, \cdots, x_n\}$, the similarity degree between two subsequences X_i^m and X_j^m of length m is calculated using the fuzzy membership function.

(3) Computing the Fuzzy Entropy: The fuzzy entropy $FuzzyEn(m, r, N)$ is computed as:

$$FuzzyEn(m, r, N) = \ln \Phi^m(r) - \ln \Phi^{m+1}(r)$$

where $\Phi^m(r)$ is the average similarity degree for subsequences of length m, r is the tolerance parameter, and N is the length of the dataset.

3. Results

3.1 Correlation Results by Water Depths

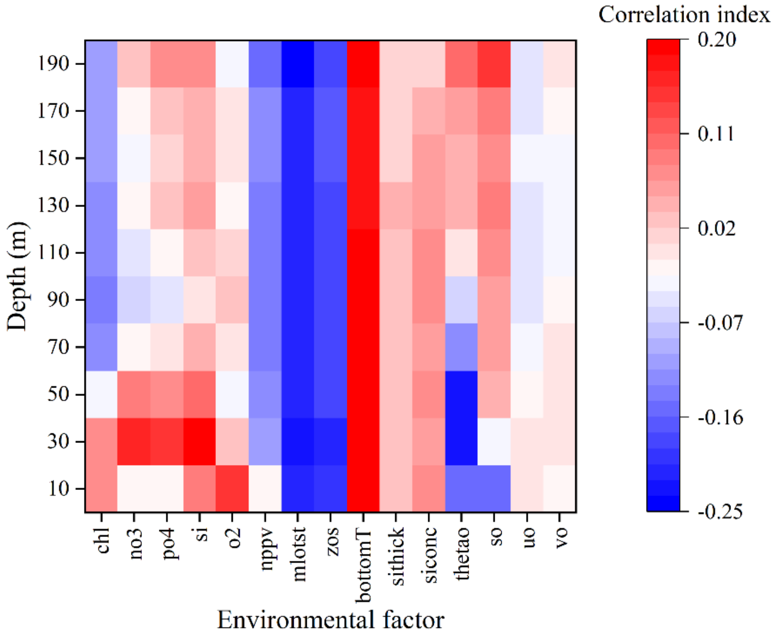

Figure 3. Correlation Heatmap of Environmental Variables and Krill Density.

The heatmap illustrates the Pearson correlation coefficients between various environmental variables and krill density across different water depths. Warm colors (red) indicate positive correlations, while cool colors (blue) represent negative correlations. The analysis reveals that variables such as Sea bottom temperature (bottomT) and silicate concentration (si) exhibit moderate positive correlations with krill density, whereas mixed layer depth (mlotst) and sea surface height (zos) show negative correlations. This visualization aids in identifying key environmental factors influencing krill distribution.

3.2 Identification of Optimal Krill Habitat Using Fuzzy Entropy and Environmental Variable Analysis

Figure 4 (left one) The variation of fuzzy entropy with water depth is shown, where lower entropy values indicate higher suitability for krill habitat. The red dashed line highlights the optimal depth, identified as the point with the minimum entropy value. This depth represents the most favorable conditions for krill survival, as it reflects the least environmental variability and stress.

Figure 4 (right one) The normalized values of key environmental variables (e.g., chlorophyll, nitrate, phosphate, temperature, and oxygen) are plotted against water depth. The red dashed line marks the optimal depth, demonstrating how these variables stabilize or reach favorable levels at this depth. The convergence of these normalized trends supports the identification of the optimal depth, as it indicates a balanced and stable environment conducive to krill habitat.

Together, these subplots provide a comprehensive analysis of the relationship between environmental conditions, water depth, and habitat suitability for krill. The integration of fuzzy entropy and normalized environmental variables offers a robust method for identifying optimal habitats in marine ecosystems.

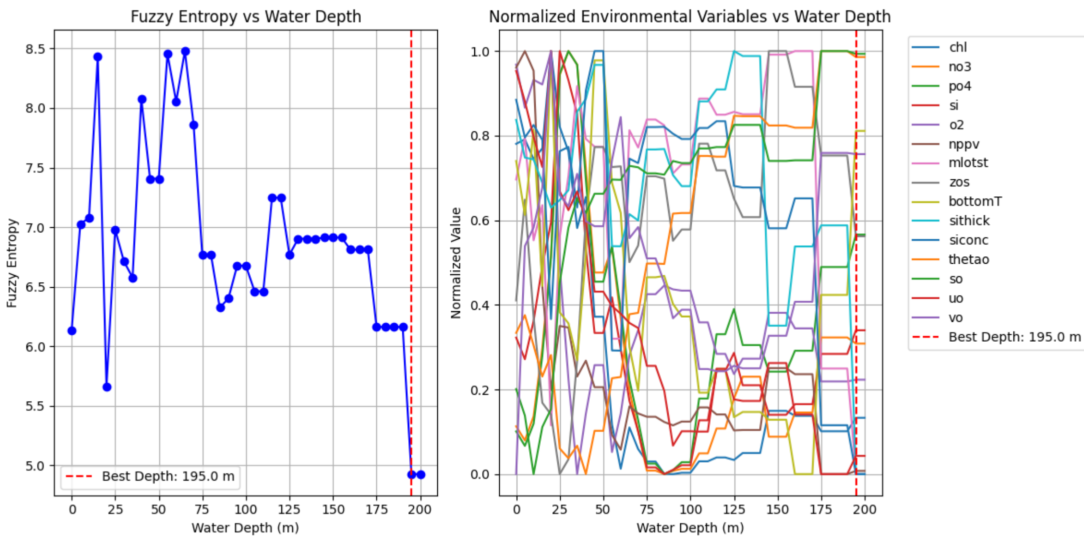

Figure 4. Relationship between Fuzzy Entropy, Environmental Variables, and Water Depth.

4. Discussions

4.1 The Impact of Different Environmental Factors on Krill Abundance

The correlation analysis revealed varying influences of environmental factors on Antarctic krill density. Mixed layer depth (mlotst) showed a moderate negative correlation (r =−0.210), suggesting that deeper mixed layers may reduce phytoplankton availability, limiting krill abundance. Sea bottom temperature (bottomT) had a positive correlation (r =0.202), indicating warmer temperatures may enhance biological activity and krill aggregation. Sea surface height (zos) exhibited a weak negative correlation (r =−0.173), potentially reflecting changes in ocean circulation affecting krill habitats. Chlorophyll concentration (chl), a proxy for phytoplankton, showed a weak positive correlation (r =0.079), highlighting the importance of food availability. Nitrate (no3) and silicate (si) concentrations also had weak positive correlations (r =0.074 and r =0.097, respectively), emphasizing their role in supporting the krill food web. In contrast, factors like eastward (uo) and northward (vo) current velocities, dissolved oxygen (o2), and net primary production (nppv) showed negligible correlations, suggesting a minimal direct impact on krill distribution. Overall, sea bottom temperature and mixed layer depth emerged as key drivers, while nutrient-related variables indirectly influenced krill abundance through the food web.

4.2 The Impact of Water Depth on Krill Abundance

Water depth plays a critical role in shaping the distribution and abundance of Antarctic krill. In this study, the most suitable water depth for krill was identified at 195.0 meters, with a fuzzy entropy value of 4.926, indicating optimal environmental conditions at this depth. Krill tends to aggregate in specific depth layers where factors such as temperature, food availability, and light conditions are favorable. The fuzzy entropy analysis highlights the complexity and variability of krill distribution across different depths, with the 195-meter depth zone exhibiting the highest suitability. This finding aligns with previous studies suggesting that mid-depth layers often provide a balance between access to phytoplankton-rich surface waters and refuge from predators [2, 9]. Understanding these depth preferences is crucial for predicting krill distribution and managing their habitats in the context of changing ocean conditions.

5. Conclusions

This study utilized fuzzy entropy and normalized environmental variables to identify the optimal water depth for krill habitat. The analysis revealed a specific depth with minimal entropy, indicating stable and favorable environmental conditions. The integration of multiple variables, such as chlorophyll, nitrate, and temperature, provided a comprehensive understanding of habitat suitability. These findings offer valuable insights for marine ecosystem management and highlight the importance of balancing environmental factors in conserving krill populations. Further research could expand this approach to other species and regions.

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