Acta Oceanol. Sin., 2024, Vol. 43, No. 5, P. 110–120
https://doi.org/10.1007/s13131-024-2328-5
http://www.aosocean.com
E-mail: ocean2@hyxb.org.cn

Quantitative analysis and prediction of the sound field convergence zone in mesoscale eddy environment based on data mining methods

Ming Li[1*†], Yuhang Liu[2†], Yiyuan Sun[3], Kefeng Liu[1]

[1] College of Advanced Interdisciplinary Studies, National University of Defense Technology, Nanjing 211101, China

[2] Jiangsu Ocean University, Lianyungang 222061, China

[3] College of Horticulture Forestry Sciences, Huazhong Agricultural University, Wuhan 430070, China

Received 8 December 2023; accepted 3 April 2024

Abstract

The mesoscale eddy (ME) has a significant influence on the convergence effect in deep-sea acoustic propagation. This paper use statistical approaches to express quantitative relationships between the ME conditions and convergence zone (CZ) characteristics. Based on the Gaussian vortex model, we construct various sound propagation scenarios under different eddy conditions, and carry out sound propagation experiments to obtain simulation samples. With a large number of samples, we first adopt the unified regression to set up analytic relationships between eddy conditions and CZ parameters. The sensitivity of eddy indicators to the CZ is quantitatively analyzed. Then, we adopt the machine learning (ML) algorithms to establish prediction models of CZ parameters by exploring the nonlinear relationships between multiple ME indicators and CZ parameters. Through the research, we can express the influence of ME on the CZ quantitatively, and achieve the rapid prediction of CZ parameters in ocean eddies. The prediction accuracy (R) of the CZ distance (mean R: 0.981 5) is obviously better than that of the CZ width (mean R: 0.872 8). Among the three ML algorithms, Gradient Boosting Decision Tree has the best prediction ability (root mean square error (RMSE): 0.136), followed by Random Forest (RMSE: 0.441) and Extreme Learning Machine (RMSE: 0.518).

Key words: convergence zone, mesoscale eddy, statistic analysis, quantitative prediction, machine learning

Citation: Li Ming, Liu Yuhang, Sun Yiyuan, Liu Kefeng. 2024. Quantitative analysis and prediction of the sound field convergence zone in mesoscale eddy environment based on data mining methods. Acta Oceanologica Sinica, 43(5): 110–120, doi: 10.1007/s13131-024-2328-5

1 Introduction

The convergence is a special phenomenon of acoustic propagation in the deep sea. When the sound source and receiver are located in the sound channel, due to the refraction of the sound wave, the sound energy will gather near the sea surface to form a ring band of high intensity and low distortion, called the convergence zone (CZ). The CZ effect can be used to achieve underwater remote detection, underwater acoustic communication, positioning and navigation. Accurate prediction of sound field CZ is of great significance to the research of oceanographic mechanism, the development of underwater acoustic equipment and military applications.

As a special phenomenon of deep-sea remote sound channel, CZ has been extensively studied by many scholars. Earlier, Hale (1961) observed the deep-sea convergence phenomenon in offshore experiments. Later, other researchers also verified the existence of the deep-sea CZ through experimental observation and theoretical analysis, and described the spatial-temporal characteristics of CZ (Urick and Lund, 1968; Zhang, 1982; Gong et al., 1987; Guan et al., 1998). The experiment results show that the formation and characteristics of CZ are closely related to the marine environment. In recent years, more and more attention has been paid to the study of the influence of ocean dynamic processes, such as mesoscale eddies, internal waves and fronts, on the deep-sea acoustic propagation.

Lawrence (1983) found that the different spatial positions of the sound source and the receiving array in the warm eddy would lead to different changes in the CZ characteristics and Heaney et al. (2011) verified this conclusion experimentally. Liu (2006) found that the presence of mesoscale eddies and fronts would cause changes in the location and intensity of the sound field CZ, and even lead to the disappearance of the CZ. Zhang et al. (2011) used the Gaussian beam ray model to analyze the differences of CZ acoustic propagation in different directions caused by the warm eddy. Liu et al. (2021b) and Li et al. (2023) found that the horizontal disturbance of the sound velocity profile caused by the cold eddy could made the CZ location move forward, the width decrease, and the gain increase. Zhu et al. (2021) found that when the warm eddy existed and the sound source is in the eddy center, the width of the CZ decreased and the location moved forward. Van Uffelen et al. (2010) found that with the development of the summer thermocline from June to October, the scattering effect of internal waves on the sound field became greater, resulting in the inversion point of CZ deeper. Zhang et al. (2022) found that with the increase of transmit-receive distance, the cumulative effect of internal waves became more significant. The

Foundation item: The National Natural Science Foundation of China under contract Nos 41875061 and 41775165.
*Corresponding author, E-mail: mingli152@163.com
†These authors contributed equally to this work.

statistical characteristics of propagation loss in shallow-sea linear internal wave environment are related to the average energy flux density, sound source frequency, sound source location and transmit-receive distance. Guo and Gao (2015) studied the propagation law of sound waves in the oceanic front and found that the span of the CZ increased significantly when there was an oceanic front. The CZ formed by the weak front has a larger span than that formed by the strong front, and the width of CZ in the weak front is larger than that in the strong front.

The above studies show that the typical mesoscale ocean systems have a significant influence on the characteristics of deep-sea CZ, which cannot be ignored. The scholars have analyzed the CZ characteristics with simulation experiments under the influence of different vertical structures of sound velocity, mesoscale eddies, internal waves, and oceanic fronts. However, the existing analysis is mostly focused on the qualitative description of the acoustic field characteristics and difference phenomenon. There are few studies about quantitatively mining and expressing the mathematical relationships between ocean environmental systems and the characteristics of sound field CZ (Fan et al., 2012).

Quantitative analysis of the influence of marine systems on the CZ features is helpful to the accurate prediction of sound field characteristics. In our research, we will focus on analyzing the of CZ parameters (distance and width) in mesoscale eddies with data mining methods including regression analysis and machine learning (ML) algorithms. Based on the different acoustic propagation scenarios constructed with the Gaussian vortex model, we carry out simulation experiments and obtain modeling samples. Then the regression model is adopted to conduct analytical analysis between the eddy conditions and CZ parameters. The sensitivity of ME to the sound field CZ is quantitatively analyzed. Finally, we adopt the ML algorithms to explore the nonlinear relationships between multiple ME indicators and CZ parameters. The prediction model based on ML algorithms is established to realize the rapid prediction of the CZ parameters in the eddy environment.

The paper is structured as follows: Section 2 briefly introduces the CZ theory and ML algorithms. Section 3 provides a detailed elaboration of the technical route of analytical analysis and quantitative prediction. Section 4 describes the specific process of the acoustic propagation simulation with varieties of mesoscale eddies. Section 5 gives a full explanation of the analytical model and prediction model of CZ parameters, and quantitatively analyzes the relationship between the eddy condition and CZ characteristics. Finally, Section 6 concludes the paper.

2 Theory and methods

2.1 *Deep-sea convergence zone*

2.1.1 *Concept of convergence zone*

The sound speed profile of deep sea has a minimum value at a certain depth, which is the channel axis. The sound speed increases from the channel axis upward with the increase of temperature, and increases from the channel axis downward with the increase of static pressure (Liu et al., 2021a). The sound speed distribution is shown in Fig. 1.

When a sound source is close to the surface, according to the Snell law, the sound rays will bend toward the vertical. In other words, the sound rays emitted by the source will bend to the bottom. The sound rays will gradually bend toward the surface after passing through the sound channel axis where the sound speed is minimum. When the sound speed near the bottom is greater than that close to the source at the sea surface, some sound rays

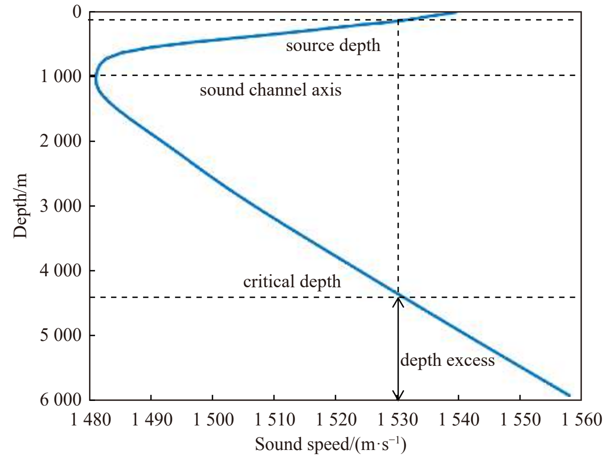

Fig. 1. The sound speed profile of deep sea.

with small grazing angles do not touch the bottom and reverse upward (Wu et al., 2022).

If the sound source is placed in the sound channel, part of the energy will be bound in the channel, which will not touch the seabed and sea surface during the propagation process. Therefore, it will not be scattered and absorbed by the boundary, and the sound can travel over very long distance. After this process, sound rays converge to form a CZ as shown in Fig. 2.

When the exit angle is 0°, the sound inversion depth is the smallest, which is the critical depth to form the CZ, called the conjugate depth. The horizontal distance of the sound ray to the sea surface is called the occurrence distance of CZ (usually refers to the distance of the first CZ). The condition for the formation of CZ is that both the source and the receiver are located in the sound channel and the water is deep enough so that the sound rays are refracted underwater and return to the surface to form the CZ. When the water depth is shallow, the sound rays are absorbed and reflected by the seafloor, inhibiting the occurrence of CZ.

2.1.2 *Feature extraction of CZ*

Distance and width are the two most important parameters of CZ. At present, two methods are usually used to determine the CZ parameters. The first method is proposed by Blatstein (1971), which defines the peak position of propagation loss gain as the position of the CZ inversion point. The distance after the peak gain where the propagation loss is greater than the peak about

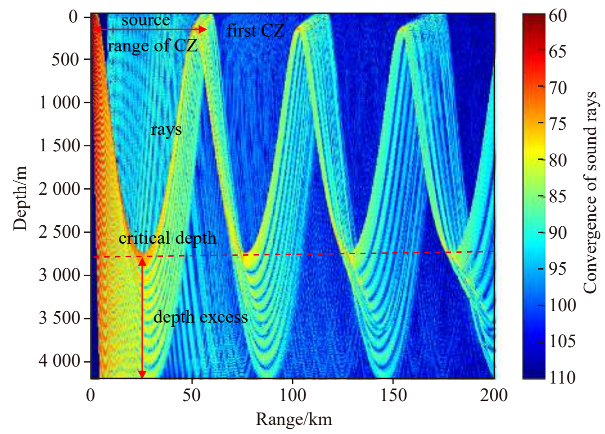

Fig. 2. The convergence of sound rays in deep sea.

10 dB is the width of the CZ. Another method is proposed by Bongiovanni et al. (1996). He determines the CZ distance and width according to the characteristic sound rays. The CZ distance is set to the position of the ray with an exit angle of 0° when it returns to 0°. Set the difference between the arrival distance of the critical sound ray and the distance of CZ as the CZ width.

The experimental results show that the two methods are consistent in determining the CZ distance, and both can reflect the location of the CZ peak gain (Zhang and Zhang, 2012; Zhao, 2015; Piao et al., 2021). However, the first method is somewhat arbitrary in the processing of the CZ width. When there is a cold eddy in the sound velocity field, the difference between the peak gain in the CZ and the propagation loss in the shadow zone is small. After due consideration, the method proposed by Bongiovanni et al. (1996) is used to extract CZ parameters in this paper.

The sound ray with an exit angle of 0° has the minimum inversion depth, and the horizontal distance from the sound ray to the sea surface is defined as the distance of the first CZ:

$$L = 2\,m\sqrt{c_0^2\sec^2\theta - c_{\rm h}^2} + 2\,m_{\rm l}\arctan\theta, \tag{1}$$

$$m = \frac{g_1 - g_2}{g_1\,g_2}, \tag{2}$$

$$m_1 = \frac{c_0}{g_1}, \tag{3}$$

where g_1 and g_2 are the average sound velocity gradients of the upper and lower layers of the sound channel axis respectively; c_0 is the sea surface sound velocity or the maximum sound velocity of the surface sound channel; $c_{\rm h}$ is the sound velocity at the axis of the sound channel; θ is the initial grazing angle of the sound line.

When $\theta = 0°$, the distance of the sound ray to the sea surface is maximum, that is

$$L_0 = 2\,m\sqrt{c_0^2 - c_{\rm h}^2}. \tag{4}$$

When $\theta = \theta_{\max}$,

$$L_{\rm m} = 2\,m\sqrt{c_0^2\sec^2\theta_{\max} - c_{\rm h}^2} + 2\,m_{\rm l}\arctan\theta_{\max}. \tag{5}$$

The width of the first CZ is defined as

$$\Delta L = L_{\rm m} - L_0. \tag{6}$$

2.2 *Modeling approach*

In this paper, data mining methods such as the regression analysis, machine learning algorithms are used to carry out the analytical analysis of CZ features and build a CZ parameter prediction model, so as to quantify the influence relationship of the ME on the CZ and achieve the rapid prediction of CZ parameters.

ML can mine the nonlinear correlation between variables from objective data. In our experiments, three ML algorithms are selected for modeling: Random Forest, Gradient Boosted Decision Tree and Extreme Learning Machine.

(1) Random Forest (RF). A decision tree (DT) is constructed recursively as a binary decision tree by constantly splitting the nodes with a squared error minimization criterion and ultimately using the mean of the leaf nodes as the predicted value. DT is suitable for dealing with interactions among features (or predictors), easy to interpret, and runs fast. Based on the idea of ensemble learning, DT is used as the base learning machine to establish an ensemble model, namely RF. The predicted value of RF is obtained by taking the mean prediction of all DTs. Balancing the error of data sets gives RF the advantage of not easy to overfit; besides that, it also has great robustness.

(2) Gradient Boosted Decision Tree (GBDT). GBDT is also a supervised learning method which takes DT as the basic unit and approximates real function step by step by way of addition model. It is an integrated tree-based algorithm like RF, but the method adopted is different. GBDT is an iterative method, each step needs to construct a new DT according to the loss function, and constantly approximates the real function through the direction of the negative gradient.

(3) Extreme Learning Machine (ELM). ELM is a novel single hidden layer feedforward neural network, overcoming the weakness of slow convergence and local optimum in conventional neural networks. However, the random setting of initial weights and threshold easily results in weak stability and poor generalization. To deal with this deficiency, Cao et al. (2012) used the self-adaptive differential (SaD) evolution algorithm to improve ELM and further proposed the SaD-ELM, which is used in our research.

3 Modeling process

In this paper, the analytical analysis and quantitative prediction of sound field CZ parameters under the ME environment are carried out. The modeling technology route is shown in Fig. 3.

Firstly, many eddies with different intensity and radius are constructed based on the Gaussian vortex model. Sound sources are placed in different locations around each eddy. Various sound propagation scenarios under ME environment are designed.

Then, the BELLHOP sound propagation model is used for simulation experiments to calculate the distribution of sound rays under different eddy conditions. The characteristic paramet-

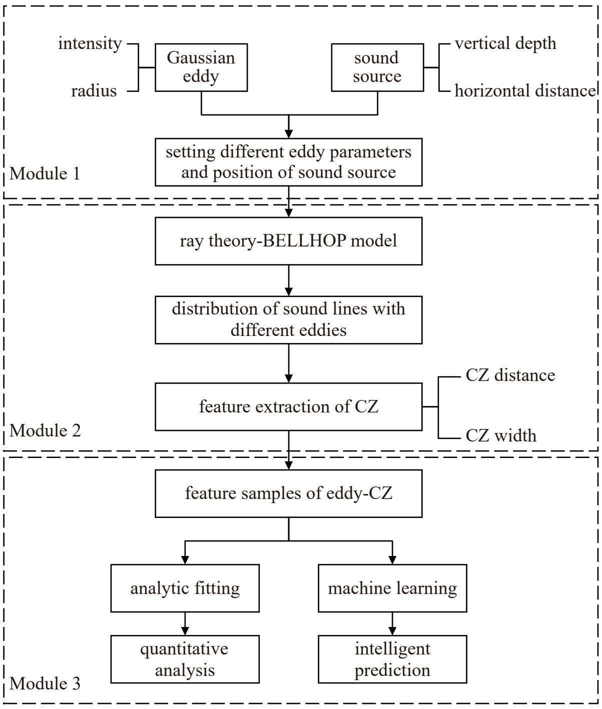

Fig. 3. The technical route of CZ parameter modeling.

ers of the first CZ are extracted, including distance and width, and generate the feature samples of the eddy condition-CZ parameter through a large number of simulation experiments.

Based on the above feature samples, two tasks are carried out: one is to establish a unitary regression model to quantitatively analyze the influence of different eddy conditions on CZ parameters; the other is to use ML algorithms to establish the mapping relationship between multiple environmental indicators and CZ parameters to achieve the rapid prediction of CZ parameters in different ME environment.

4 Acoustic propagation modeling in the mesoscale eddy

Different sound propagation scenarios under different mesoscale eddies environment are designed and acoustic propagation simulation experiments are carried out to obtain parameters of CZ. Eddy parameters and sound source positions are set as shown in Table 1.

The other eddy parameters remain unchanged in the modeling: the depth of the eddy center is 275 m; the amplitude is 200 m. Figure 4 shows the sound propagation scenarios with different eddy radius and different sound source location.

Based on different sound propagation scenarios, the sound propagation model is used to calculate the sound field characteristics. As we all known, the acoustic propagation models suitable for horizontally non-uniform conditions mainly include ray models, adiabatic normal mode models, coupled normal mode models, and parabolic equations. The ray theory model is the earliest and most widely used modeling theory for acoustic propagation. The classic ray acoustic theory assumes that the energy of the sound field is transmitted by sound rays. The path of the sound ray represents the path of sound wave propagation, and the energy carried by the sound ray represents the acoustic energy of sound propagation.

However, the traditional ray models are limited by the high-frequency approximation and cannot effectively calculate the propagation loss near the caustic line. The BELLHOP model based on the Gaussian beam ray tracing algorithm is proposed (Cong, 2010), which effectively improves the traditional ray theory and solves the calculation difficulties of the sound propagation in the shadow zone and caustic zone. Due to its advantages such as clear physical image, fast calculation speed and broad applicability, the BELLHOP model has been widely used in underwater sound propagation. We use this model for acoustic propagation calculation.

Figure 5 shows the sound propagation loss and sound ray distribution when the warm eddy intensity is 10 m/s, the eddy radius is 100 km, the sound source depth is 175 m, and the horizontal distance of the sound source is 140 km. Figure 6 shows that, with the same position of the sound source, the sound propagation loss and the sound line distribution when there is no eddy. It can be intuitively found that the CZ characteristics change significantly, so it is necessary to quantitatively analyze the influence of eddies on the CZ.

We calculate the acoustic propagation characteristics of all scenarios and extract the parameters of the first CZ, obtaining a total of 95 670 modeling samples. Each sample contains CZ distance/width and their corresponding eddy parameters, covering the range of cold/warm eddy intensity with –50 m/s to +50 m/s (where + indicates warm eddy and – indicates cold eddy), eddy radius with 20–300 km, sound source depth with 100–400 m, and the horizontal distance of the sound source with 0–150 km.

5 Experiments and analysis

Based on the above feature samples, two tasks are carried out: one is to build a unitary regression model between eddy conditions and CZ parameters; the other is to use ML algorithms to establish the mapping relationship between multiple eddy indicators and CZ parameters to achieve the rapid prediction of CZ parameters.

5.1 *Analytical analysis based on the regression model*

In this paper, the polynomial regression method is used to analyze the relationship between the CZ characteristics and the ME conditions. We use linear regression model and quadratic function regression model to conduct regression modeling between them. The regression equation is established, and the sensitivity analysis of CZ parameters is conducted based on the optimal regression model.

(1) CZ distance-eddy intensity

The CZ distance is taken as the dependent variable (y) and the eddy intensity as the independent variable (x). The polynomial fitting is carried out and the results with different depth of sound source are shown in the Table 2, where R^2 represents determination coefficient, F represents F-statistic value, Sig. represents significance, and RMSE is root mean square error.

The results show that under different sound source depth conditions, the determination coefficient between the CZ distance and the eddy intensity is very significant with the two regression models ($R^2 > 0.95$), and the model has a high degree of good fitting. In the F-test, the observed values of the linear regression model are greater than those of the quadratic regression model. The significance test values of the two regression models are both 0, indicating that there is a significant difference between the partial regression coefficient and random interference in regression analysis. Therefore, the linear relationship between the eddy intensity and the CZ distance is significant.

The influence of the eddy intensity on the CZ distance is linear. According to the linear regression equation, the CZ distance increases with the increase of warm eddy intensity, and decreases with the increase of cold eddy intensity. In the equation, the coefficient of eddy intensity is the influence factor of the existence of eddy. When the sound source is located at a shallow depth, the influence of eddy intensity on the CZ distance is small. The deeper the location of the sound source, the larger the coefficient of eddy intensity, indicating that the eddy has a more intense effect on the CZ distance. When the sound source is located at the depth of 300 m, the eddy intensity changes by 2 m/s

Table 1. The description of eddy parameters and sound source position

Parameter	Definition	Setting
Eddy intensity/(m·s^{-1})	it is characterized by the sound velocity difference between the eddy center and the edge	value range is –50 m/s to +50 m/s, gap is +5 m/s; + indicates warm eddy and – indicates cold eddy
Eddy radius/km	it is characterized by the horizontal distance between the eddy center and the edge	value range is 20 km to 300 km, gap is 20 km
Depth of sound source/m	literal meaning	value range is 100 m to 400 m, gap is 20 m
Distance of sound source/km	it is characterized by the horizontal distance of the sound source from the eddy center (vertical central axis)	value range is 0 km to 150 km, gap is 15 km

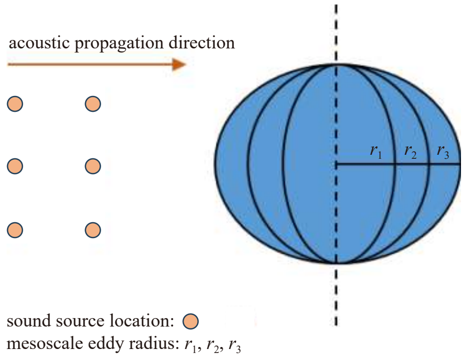

Fig. 4. Different sound propagation scenarios.

(sound velocity difference), and the distance of the first CZ changes by about 200 m.

(2) CZ distance-eddy radius

The CZ distance is taken as the dependent variable (y) and the eddy radius as the independent variable (x). The results of polynomial fitting are shown in the Table 3.

The results show that under different sound source depth conditions, the determination coefficient of the linear regression model ($R^2 > 0.85$) is very significant less than that of the quadratic regression model ($R^2 > 0.95$). In the F-test, the observed values of the linear regression model are less than those of the quadratic regression model. The significance test values of the two regression models are both 0, indicating that there is a significant difference between the partial regression coefficient and random interference in regression analysis. Therefore, the quadratic function relation between the eddy radius and the CZ distance is significant.

According to the quadratic function regression equation, the constant term represents the distance of the first CZ when there is no eddy. The coefficient of eddy radius is the influence factor of eddies. The coefficient of eddy radius is very small and it is two orders of magnitude smaller than the coefficient of eddy intensity in Table 2. Therefore, the influence of eddy intensity on the CZ

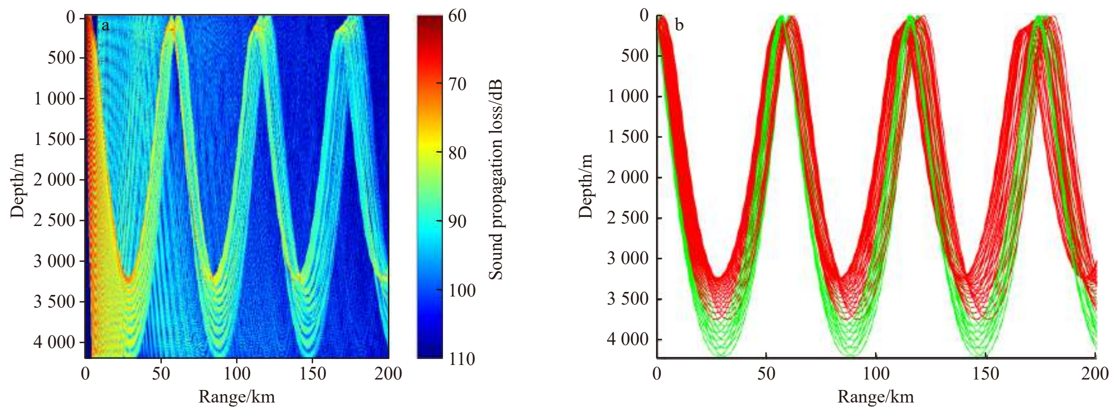

Fig. 5. Characteristics of sound propagation with a warm eddy: the sound propagation loss (a) and sound ray (b) distribution. In b, the red line represents the refracted sound, and the green line represents the reflected sound.

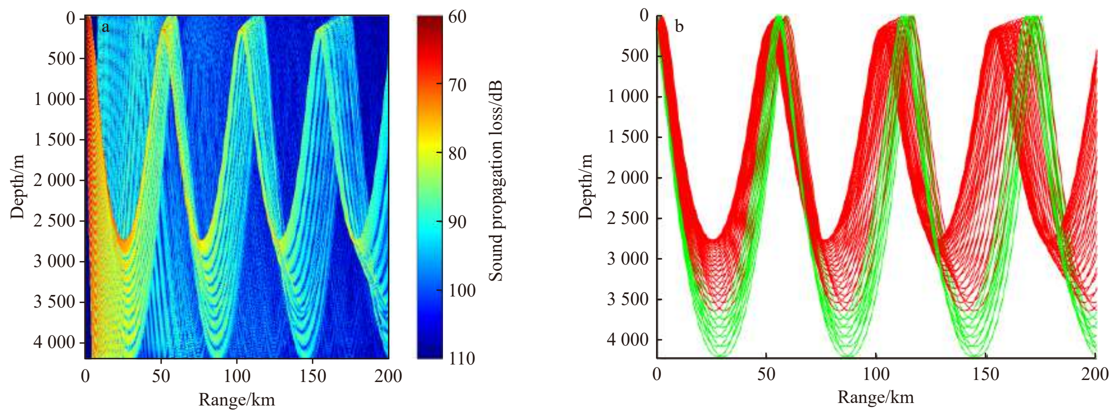

Fig. 6. Characteristics of sound propagation with no eddy: the sound propagation loss (a) and sound ray (b) distribution. In b, the red line represents the refracted sound, and the green line represents the reflected sound.

Table 2. Regression analysis between CZ distance and eddy intensity

Model	Depth/m	Regression equation	R^2	F	Sig.	RMSE
Linear regression model	100	$y = 0.076\ 15x + 53.15$	0.992	14 598.965	0	0.226
	200	$y = 0.087\ 75x + 49.94$	0.998	19 823.564	0	0.307
	300	$y = 0.099\ 79x + 47.14$	0.988	10 479.997	0	0.181
Quadratic regression model	100	$y = 0.000\ 24x^2 + 0.076\ 15x + 52.92$	0.999	13 874.476	0	0.079
	200	$y = 0.000\ 32x^2 + 0.087\ 75x + 49.64$	0.998	14 462.807	0	0.121
	300	$y = 0.000\ 17x^2 + 0.049\ 79x + 46.98$	0.996	9 134.502	0	0.096

Table 3. Regression analysis between CZ distance and eddy radius

Model	Depth/m	Regression equation	R^2	F	Sig.	RMSE
Linear regression model	100	$y = 0.012\ 53x + 54.59$	0.752	1 124.873	0	0.625
	200	$y = 0.016\ 51x + 51.37$	0.839	1 952.309	0	0.626
	300	$y = 0.008\ 86x + 48.02$	0.793	1 267.598	0	0.392
Quadratic regression model	100	$y = -0.000\ 11x^2 + 0.041\ 02x + 52.93$	0.963	11 269.375	0	0.244
	200	$y = -0.000\ 12x^2 + 0.044\ 71x + 49.73$	0.973	14 633.754	0	0.261
	300	$y = -0.000\ 11x^2 + 0.027\ 19x + 46.96$	0.979	15 124.561	0	0.127

distance is more sensitive.

According to the monotone property of the quadratic function, when the depth of the sound source is 300 m, the CZ distance increases with the increase of the eddy radius in the interval of [20 km,186.3 km]; the CZ distance slightly decreases with the increase of the eddy radius in the interval of [186.3 km, 300 km]. When the eddy radius changes by 10 km, the CZ distance changes by about 260 m. Based on quadratic function regression equation, the relationship between the CZ distance and eddy radius can be quantitatively analyzed.

(3) CZ width-eddy intensity

With the same modeling idea, we build the polynomial fitting relationship between the CZ width (y) and eddy intensity (x), and the results are shown in the Table 4.

The results show that the influence relationship between the CZ width and the eddy intensity is quite different with different sound source depth. When the depth of the sound source is relatively shallow (100 m, 200 m), the determination coefficient is very significant under the two regression models ($R^2 > 0.9$). In the F-test, the observed values of the linear regression model are greater than those of the quadratic function regression model, so the linear relationship between the CZ width and the eddy intensity is more significant. By contrast, when the position of the sound source is deep (300 m), the linear relationship and quadratic function relationship between the two are very weak.

When the position of the sound source is shallow, the influence of eddy intensity on the CZ width is linear. According to the linear regression equation, the CZ distance increases with the increase of warm eddy intensity, and decreases with the increase of cold eddy intensity. In the equation, the coefficient of eddy intensity is the influence factor of the mesoscale eddy. The constant term represents the CZ distance in the absence of an eddy. When the depth of the sound source is 200 m, the eddy intensity changes by 2 m/s, and the CZ width changes by 90 m. The relationship between the CZ width and the eddy intensity can be described quantitatively based on the regression equation.

(4) CZ width-eddy radius

We build the polynomial fitting relationship between the CZ width (y) and eddy radius (x), and the results are shown in the Table 5.

The results show that the R^2 is less than 0.8 for both linear equations and quadratic equations. The small F-value and the large RMSE indicate that both the linear relationship and quadratic function relationship between the CZ width and eddy radius are very weak. Therefore, the nonlinear effect between them is complicated and it is difficult to describe the relationship by the unitary regression model.

5.2 *Intelligent prediction of CZ parameters*

In the above section, the sensitivity analysis is carried out by establishing unitary regression models, and the relationships between the characteristics of the first CZ and the eddy parameters are quantitatively analyzed: there is a significant linear relationship between the CZ distance and the eddy intensity, and a significant quadratic function relationship between the CZ distance and the eddy radius. In contrast, the linear and quadratic relationship between the CZ width and the eddy radius is very weak.

Therefore, the influence relationships between the CZ parameters and the ME conditions are very complicated. The comprehensive influence of multiple environmental factors on CZ parameters cannot be accurately described by the single variable regression equation. In order to achieve accurate quantitative analysis and fast calculation of CZ features under the eddy envir-

Table 4. Regression analysis between the CZ width and eddy intensity

Model	Depth/m	Regression equation	R^2	F	Sig.	RMSE
Linear regression model	100	$y = -0.032\ 99x + 5.979$	0.973	12 531.632	0	0.264
	200	$y = -0.042\ 28x + 9.829$	0.978	13 105.415	0	0.256
	300	$y = -0.066\ 83x + 14.51$	0.184	/	/	4.549
Quadratic regression model	100	$y = 0.000\ 22x^2 - 0.032\ 99x + 5.77$	0.942	9 975.143	0	0.183
	200	$y = 0.000\ 17x^2 - 0.042\ 28x + 9.67$	0.966	10 132.472	0	0.211
	300	$y = 0.002\ 92x^2 - 0.066\ 83x + 11.68$	0.454	/	/	3.787

Note: / indicates invalid value.

Table 5. Regression analysis between the CZ width and eddy radius

Model	Depth/m	Regression equation	R^2	F	RMSE
Linear regression model	100	$y = -0.001\ 97x + 5.022$	0.411	/	0.254
	200	$y = -0.004\ 75x + 8.996$	0.721	1 024.143	0.256
	300	$y = 0.005\ 16x + 12.81$	0.789	1 322.219	0.231
Quadratic regression model	100	$y = 0.000\ 032x^2 - 0.012\ 43x + 5.63$	0.788	1 387.458	0.133
	200	$y = 0.000\ 019x^2 - 0.011\ 03x + 9.36$	0.789	1 269.655	0.226
	300	$y = -0.000\ 001\ 5x^2 - 0.005\ 4x + 12.82$	0.787	1 463.914	0.236

Note: / indicates invalid value.

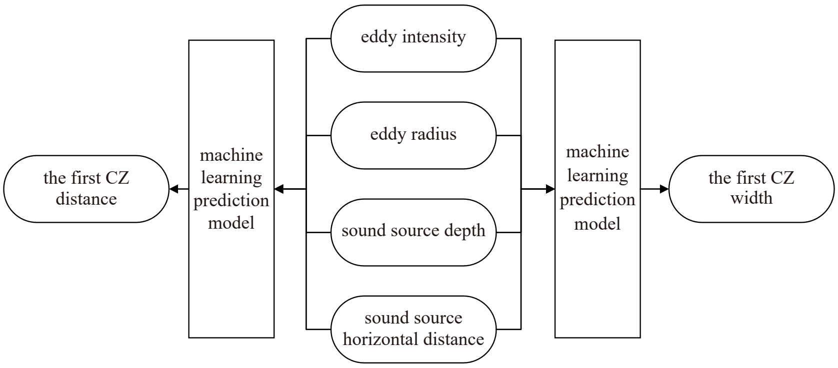

Fig. 7. The input and output of ML-based prediction model.

onment, we adopt ML algorithms to mine the nonlinear relationship between multiple eddy factors and CZ parameters, establishing CZ prediction models.

(1) ML-based prediction model

The input of the prediction model is the eddy intensity, eddy radius, depth of sound source and horizontal distance of sound source from the eddy center; the output is the first CZ distance and the first CZ width respectively, as shown in Fig. 7.

We adopt the RF algorithm, GBDT algorithm and SaD-ELM algorithm to construct prediction models, and the technical process is shown in Fig. 8.

Firstly, the feature samples are normalized and divided into training sets and test sets. Then, we set parameters of the three ML algorithms and complete the training of prediction model. Parameter calibrations are subjected to sensitivity analysis, which is conducted by "*GridSearchCV*" function provided by scikit-learn module, which is a function library for ML including all kinds of classification, regression and clustering algorithms. The best parameters are shown in the Table 6. Finally, the test samples are input into the ML model and the prediction results are output. Through comparative analysis, the prediction ability of the model is compared, and the applicability of ML algorithms in the prediction of sound field CZ parameter is discussed.

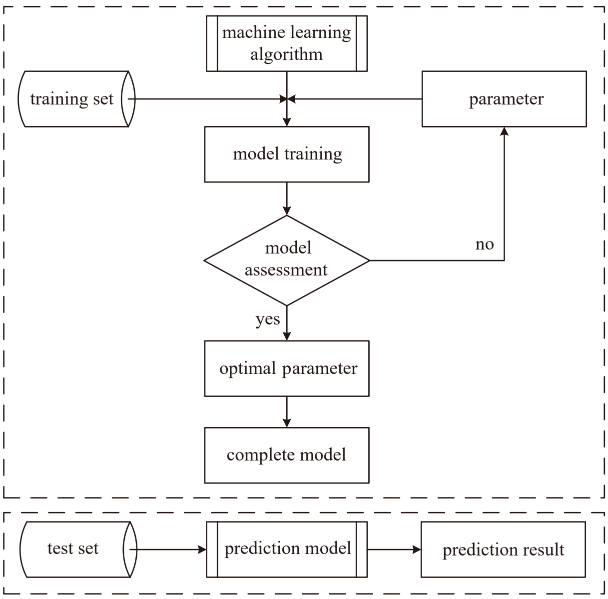

Fig. 8. The technical process of ML-based prediction model.

(2) Analysis of predicting results

According to the Eq. (7), the relative error (RE) of the predicted value of CZ parameters is calculated, and the result is shown in Figs 9–14.

$$\mathrm{RE} = \frac{|\hat{y} - y|}{y} \times 100\%, \tag{7}$$

where $\hat{y}$ is the predicted value and y is the original value.

The results show that the three ML-based models have good prediction ability on the first CZ distance, and the RE of predicted results are all less than 10%. Among them, GBDT has the best prediction accuracy (RE < 2%), followed by RF (RE < 5%) and ELM (RE < 8%).

The prediction ability for the first CZ width is not so desirable, there are a certain number of test samples with RE greater than 30%. GBDT and RF have similar prediction accuracy, the predicted results with RE > 30% accounts for about 5%, which can be accepted. BPNN has the lowest prediction accuracy, the predicted results with RE > 30% accounts for about 9%.

To investigate the performances for the above prediction models quantitatively, different error measures including the correlation coefficient (CC), RMSE, and Nash-Sutcliffe (NSE) are employed as evaluation criteria. We do not repeat CC and RMSE in consideration of space. NSE is explained as follows:

$$\mathrm{NSE} = 1 - \frac{\sum\limits_{i=1}^{n} \left(\hat{h}_i - h_i\right)^2}{\sum\limits_{i=1}^{n} \left(h_i - h_{\mathrm{m}}\right)^2}, \tag{8}$$

Table 6. Parameters set of the three ML algorithms

ML algorithm	Parameter setting
RF	the number of decision trees, the maximum depth of each tree, and the number of node samples are set as 100, 30, and 10; the remaining parameters are left with the default values
GBDT	the maximum depth of the tree is 5; maximum iteration is 5; learning rate is 0.1; the remaining parameters are left with the default values
SaD-ELM	the number of hidden layers is 3; the number of neurons in each hidden layer is 10; the excitation function is "sig."; the population number, variation probability and crossover probability are set as 30, 0.5, and 0.4; the remaining parameters are left with the default values

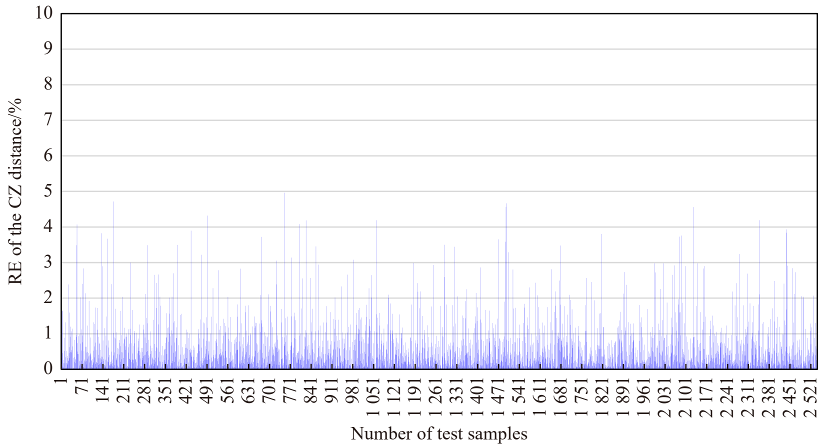

Fig. 9. The RE of the predicted CZ distance with RF.

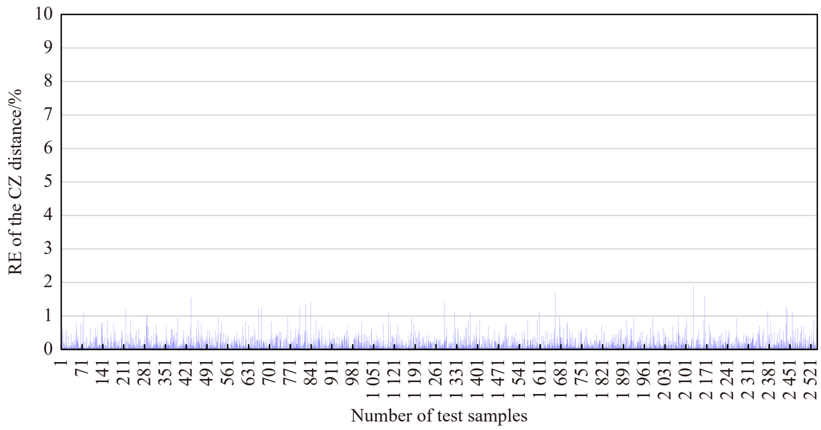

Fig. 10. The RE of the predicted CZ distance with GBDT.

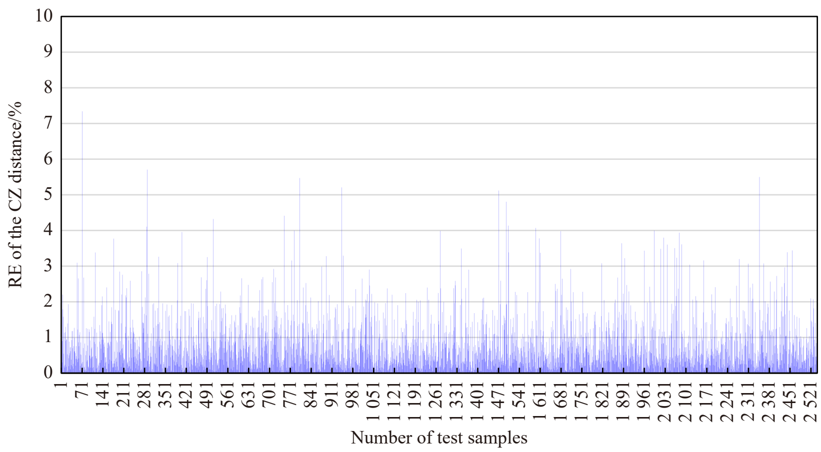

Fig. 11. The RE of the predicted CZ distance with SaD-ELM.

where $\widehat{h_i}$ is the predicted value, h_i is the test value, $h_{\rm m}$ is the mean value of h_i, i represents the sample number, and n represents the length of test time series. The RMSE is a good measure for evaluating the performance of a model because RMSE is proportional to the observed mean. Therefore, NSE compares the goodness of fit between the observed and predicted data. A high value of NSE (up to one) indicates high efficiency of the model (Duan et al., 2016).

As can be seen from the Table 7, the prediction performance of the three ML algorithms on the CZ distance is good: CC > 0.95, NSE > 0.9, RMSE < 0.5, which is obviously better than the prediction of the CZ width, indicating that the ML algorithm can better mine the nonlinear relationship between multiple eddy conditions and the CZ distance. Among the three ML prediction models, GBDT has the best prediction ability, followed by RF and ELM, which indicates that GBDT has the strongest ability to fit nonlinear relations.

In order to further test the prediction accuracy of CZ features

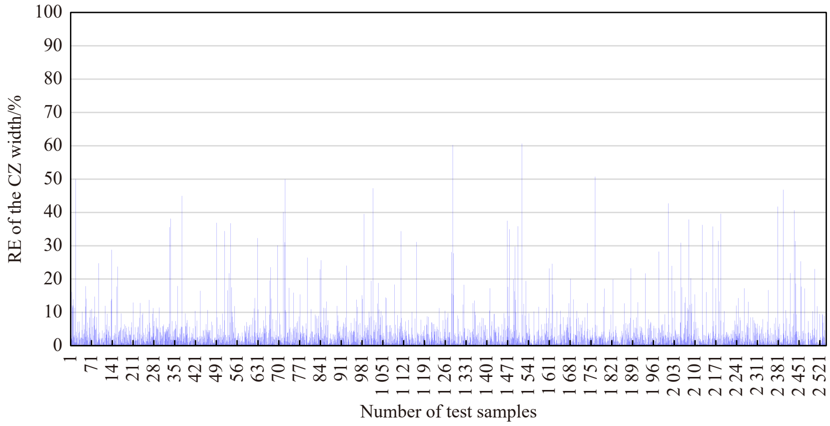

Fig. 12. The RE of the predicted CZ width with RF.

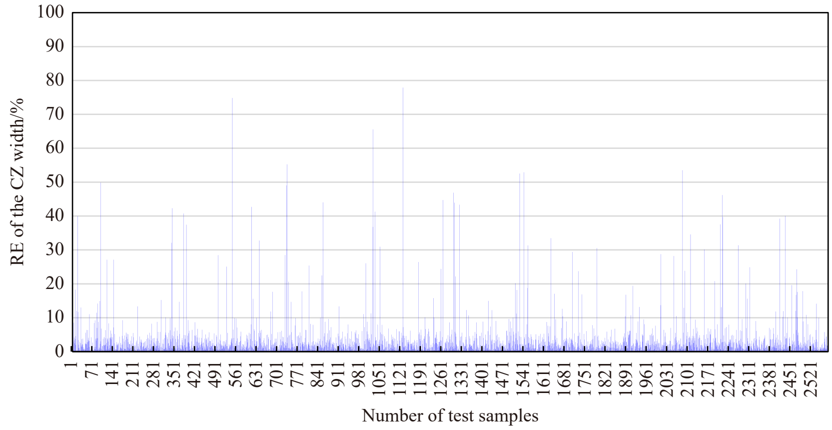

Fig. 13. The RE of the predicted CZ width with GBDT

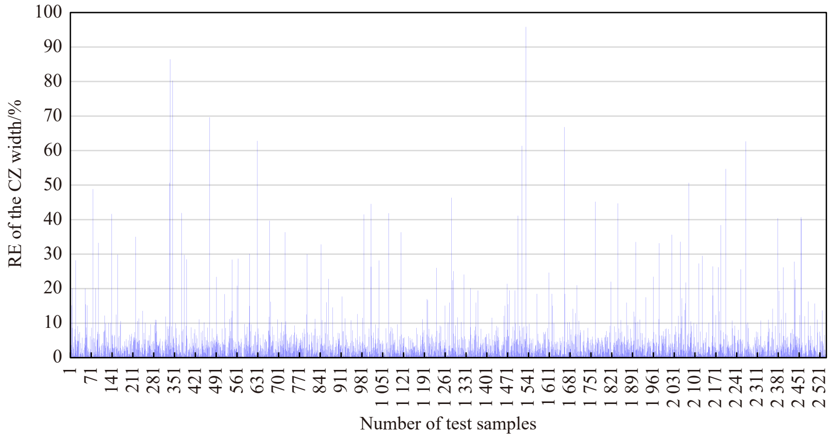

Fig. 14. The RE of the predicted CZ width with SaD-ELM

under real eddy conditions, we carry out the prediction experiments with measured data and reanalysis data. The sea area east of the Luzon Strait is selected to identify the mesoscale eddies based on satellite altimeter data, and the center location, eddy intensity and eddy radius are extracted.

Five eddies (A, B, C, D, and E) are selected for testing experiments. The three-dimensional salinity and temperature fields around the eddies (spatial range: 3° × 3°) are extracted from the Hybrid Coordinate Ocean Model (HYCOM) data. We use the data for sound propagation simulation and extract CZ parameters.

Table 7. Error measures of the predicted CZ parameters

CZ parameter	Assessing indicator	RF	GBDT	SaD-ELM
CZ distance	RMSE	0.441 2	0.135 3	0.518 2
	CC	0.977 1	0.998 2	0.969 4
	NSE	0.914 9	0.982 9	0.913 4
CZ width	RMSE	1.334 5	1.309 3	1.364 2
	CC	0.873 3	0.878 2	0.867 1
	NSE	0.604 7	0.623 1	0.502 3

Meanwhile, we use GBDT algorithm to predict the CZ parameters by input conditions of real eddies. The comparison between the predicted results and the simulation results is shown in the Table 8.

Table 8. CZ parameters calculated by ML and simulation

Eddy	Distance of the first CZ/km		Width of the first CZ/m	
	GBDT	BELLHOP	GBDT	BELLHOP
Eddy A	56.3	63.9	9.2	4.8
Eddy B	60.5	62.3	11.3	8.3
Eddy C	57.1	59.3	9.5	5.2
Eddy D	52.8	61.7	10.9	6.4
Eddy E	55.6	63.8	12.1	7.2

Using the eddy parameters extracted from the measured ME data, the prediction accuracy of CZ parameters with ML algorithm varies from eddy to eddy. The prediction of CZ distance for Eddies B and C is good, while the prediction of other eddies is poor. It can be preliminarily concluded that the ML-based prediction model has a general ability.

Further analysis of the reasons for the unstable prediction performance: when we constructed a Gaussian eddy, the horizontal distribution of temperature and salinity outside the eddy is uniform, but the horizontal distribution is uneven in the actual marine environment, resulting in poor prediction of CZ parameters under the measured eddy environment.

6 Conclusions

The mesoscale eddy has a significant influence on the acoustic propagation. This paper attempts to use mathematical modeling methods to quantitatively mine the relationship between the ME characteristics and the CZ parameters. We use the Gaussian vortex model to construct sound propagation scenarios with different eddy conditions. With a large number of simulation samples, we use data mining approaches including regression analysis and ML algorithms to carry out analytical analysis of the relationship between the eddy and the first CZ features, building the prediction model of CZ parameters. The conclusions are as follows:

(1) The relationships between the characteristic parameters of the first CZ and the eddy conditions are quantitatively analyzed: there is a significant linear relationship between the CZ distance and the eddy intensity, and a significant quadratic function relationship between the CZ distance and the eddy radius. Besides, the influence of eddy intensity on the CZ width is linear when the position of the sound source is shallow. In contrast, both the linear and quadratic relationship between the CZ width and the eddy radius are very weak.

(2) Three ML algorithms (RF, GBDT, and SaD-ELM) have obviously better prediction accuracy of the CZ distance compared with the CZ width, indicating that the ML algorithm can better fit the nonlinear relationship between multiple eddy conditions and the CZ distance. Among the three ML-based prediction models, GBDT has the best prediction ability, followed by RF and SaD-ELM.

Our research can quantify the relationship between the mesoscale eddies and the CZ characteristics, and realize the rapid prediction of the CZ parameters. However, it needs to be noted that for the prediction of CZ parameters under real mesoscale eddies environment, the prediction ability of our proposed ML-based model is unstable. In the follow-up study, we will attempt to carry out mathematical modeling based on the measured eddies, instead of the ideal Gaussian eddy.

References

Blatstein I M. 1971. Calculations of underwater explosion pulses at caustics. The Journal of the Acoustical Society of America, 49(5B): 1568–1579, doi: 10.1121/1.1912534

Bongiovanni K P, Siegmann W L, Ko D S. 1996. Convergence zone feature dependence on ocean temperature structure. The Journal of the Acoustical Society of America, 100(5): 3033–3041, doi: 10.1121/1.417115

Cao Jiuwen, Lin Zhiping, Huang Guangbin. 2012. Self-adaptive evolutionary extreme learning machine. Neural Processing Letters, 36(3): 285–305, doi: 10.1007/s11063-012-9236-y

Cong Hongri. 2010. Study on general simulation model of searching effectiveness of sonobuoy array. System Simulation Technology (in Chinese), 6(2): 104–109

Duan W Y, Han Y, Huang L M, et al. 2016. A hybrid EMD-SVR model for the short-term prediction of significant wave height. Ocean Engineering, 124: 54–73, doi: 10.1016/j.oceaneng.2016.05.049

Fan Peiqin, Da Lianglong, Li Yuyang. 2012. Research on characteristic parameter computation method of convergence zones in deep ocean. Ocean Technology (in Chinese), 31(4): 23–25

Gong Min, Xiao Jinquan, Wang Mengxin, et al. 1987. An experimental investigation of turning-point convergence-zones in a deep sound channel in the South China Sea. Acta Acustica (in Chinese), 12(6): 417–423

Guan Dinghua, Zhang Renhe, Sun Zhenge, et al. 1998. Spatial coherence of sound in convergence zones and shallow zones in the South China Sea. The Journal of the Acoustical Society of America, 103(S5): 2856

Guo Tingting, Gao Wenyang. 2015. Phenomenon of ocean front and it impact on the sound propagation. Marine Forecasts (in Chinese), 32(5): 80–88

Hale F E. 1961. Long-range sound propagation in the deep ocean. The Journal of the Acoustical Society of America, 33(4): 456–464, doi: 10.1121/1.1908691

Heaney K D, Campbell R L, Murray J J, et al. 2011. Detection performance modeling and measurements for convergence zone (CZ) propagation in deep water. The Journal of the Acoustical Society of America, 130(S4): 2530

Lawrence M W. 1983. Modeling of acoustic propagation across warm-core eddies. The Journal of the Acoustical Society of America, 73(2): 474–485, doi: 10.1121/1.388982

Li Ming, Liu Kefeng, Li Hongchen, et al. 2023. Quantitative analysis on the influence of the oceanic front on underwater acoustic detection with investigated marine data. Journal of Marine Science and Engineering, 11(8): 1574, doi: 10.3390/jmse11081574

Liu Qingyu. 2006. The research of wave propagation in ocean environment with mesoscale phenomena (in Chinese)[dissertation]. Harbin: Harbin Engineering University

Liu Dai, Li Zhenglin, Wang Guangxu, et al. 2021a. Sound propagation with undulating bottom in shallow water. Journal of Marine Science and Engineering, 9(9): 1010, doi: 10.3390/jmse9091010

Liu Jiaqi, Piao Shengchun, Gong Lijia, et al. 2021b. The effect of mesoscale eddy on the characteristic of sound propagation. Journal of Marine Science and Engineering, 9(8): 787, doi: 10.3390/jmse9080787

Piao Shengchun, Li Ziyang, Wang Xiaohan, et al. 2021. Lower turning point convegence zone in deep water with an incomplete channel. Acta Physica Sinica (in Chinese), 70(2): 024301, doi: 10.7498/aps.70.20201375

Urick R J, Lund G R. 1968. Coherence of convergence zone sound. The Journal of the Acoustical Society of America, 43(4): 723–729, doi: 10.1121/1.1910888

Van Uffelen L J, Worcester P F, Dzieciuch M A, et al. 2010. Effects of upper ocean sound-speed structure on deep acoustic shadow-zone arrivals at 500- and 1000-km range. The Journal of the Acoustical Society of America, 127(4): 2169–2181, doi: 10.1121/1.3292948

Wu Shuanglin, Li Zhenglin, Qin Jixing, et al. 2022. The effects of sound speed profile to the convergence zone in deep water. Journal of Marine Science and Engineering, 10(3): 424, doi: 10.

3390/jmse10030424

Zhang Renhe. 1982. Turning-point convergence-zones in underwater sound channel (II) A generalized ray theory. Acta Acustica (in Chinese), 7(2): 75–87

Zhang Qingqing, Li Zhenglin, Ren Yun, et al. 2022. Sound field statistical characteristics caused by linear internal waves in Dongsha sea area of the South China Sea. Acta Acustica (in Chinese), 47(2): 198–209

Zhang Xin, Zhang Xiaoji. 2012. Theory and Application of Underwater Acoustic Communication (in Chinese). Xi'an: Northwestern Polytechnical University Press, 23–29

Zhang Xu, Zhang Jianxue, Zhang Yonggang, et al. 2011. Effect of acoustic propagation in convergence zone under a warm eddy environment in the western South China Sea. The Ocean Engineering (in Chinese), 29(2): 83–91

Zhao Yue. 2015. Study on sound propagation through a mesoscale eddy environment (in Chinese)[dissertation]. Qingdao: Ocean University of China

Zhu Fengqin, Zhang Haigang, Qu Ke. 2021. Influence of mesoscale warm eddies on sound propagation in the northeastern South China Sea. Journal of Harbin Engineering University (in Chinese), 42(10): 1496–1502