Selection Optimal Method of Evaporation Duct Model Based on Sensitivity Analysis

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ABSTRACT: The evaporation duct is an abnormal refractive phenomenon with wide distribution and frequency occurrence at the boundary between the atmosphere and the ocean, which directly affects electromagnetic wave propagation. In recent years, the use of meteorological and hydrological data to predict the evaporation duct height has become an emerging and promising approach. There are some evaporation duct models that have been proposed based on the Monin–Obukhov similarity theory. However, each model adopts different stability functions and roughness length parameterization methods, so the prediction accuracies are different under different environmental conditions. To improve the prediction accuracy of the evaporation duct under different environmental conditions, a model selection optimization method (MSOM) of the evaporation duct model is proposed based on sensitivity analysis. According to the sensitivity of each model to input parameters analyzed by the sensor observation accuracy, curve graph, and Sobol sensitivity, the model input parameters are divided into several intervals. Then the optimization model is selected in different intervals. The model was established using numerical simulation data from local areas in the South China Sea, and its accuracy was verified by the observational data from the offshore observation platform located in the South China Sea. The results show that the MSOM can effectively improve the prediction accuracy of the evaporation duct height. Under unstable conditions, the maximum relative error is reduced by 7.1%, and under stable conditions, the relative error is reduced by 10.7%.

SIGNIFICANCE STATEMENT: The evaporation duct height has a significant effect on marine radar or wireless apparatus applications. To obtain the evaporation duct height, there are some evaporation duct models that have been proposed. However, different evaporation duct models are applicable to different meteorological and hydrological environments. A single model cannot achieve accurate evaporation duct height predictions in all environments. We propose a model selection optimization method of the evaporation duct model based on sensitivity analysis. This method can dynamically select the optimal model according to different meteorological and hydrological environment, and improve the prediction accuracy of the evaporation duct height. Under unstable conditions, the maximum relative error is reduced by 7.1%, and under stable conditions, the relative error is reduced by 10.7%.

KEYWORDS: Boundary layer; Air-sea interaction; Atmosphere; In situ atmospheric observations

1. Introduction

The evaporation duct occurs because of the atmospheric stratification formed by the rapid decrease of water vapor with height near the sea surface. The ocean–atmosphere interaction often generates an evaporation duct. Research shows that the occurrence probability of an evaporation duct exceeds 80% in the South China Sea (Yang et al. 2017). Evaporation duct can cause the anomalous propagation of electromagnetic (EM) waves, especially in the microwave band (Lentini and Hackett 2015). As shown in Fig. 1, the evaporation duct parameters—height (EDH), strength (EDS)—directly affect the transmission path of EM waves on the sea surface (Karabas et al. 2021). Therefore, accurate prediction of evaporation duct parameters is of great significance to maritime radio communications and radar target detection (Zaidi et al. 2018; Karabas et al. 2021; Zhang et al. 2016b).

Refraction, the cause of evaporation ducts phenomenon, can be characterized by the vertical gradients of the atmospheric refractive index \( n \). Additionally, to more convenient represent and account for the curvature of Earth, \( n \) is usually replaced with modified refractivity \( M \), which is related to atmospheric pressure \( AP \) (hPa), air temperature \( AT \) (K), partial pressure of water vapor \( e \) (hPa), and the height above sea surface \( z \) (m) through the following formula:

\[
M = 77.6 \frac{AP}{AT} - 5.6 \frac{e}{AT} + 3.73 \frac{e}{AT^2} + 0.157z. \tag{1}
\]

When using multiple meteorological observational data from different heights to calculate the EDH, the least squares fitting method is usually used to obtain the corresponding vertical profile of \( M \) (Babin et al. 1997). This profile is based on a log-linear function given by

\[
M = f_0 z - f_1 \ln(z + 0.001) + f_2. \tag{2}
\]

The constant 0.001 is added to prevent \( \ln(0) \) from appearing at sea surface. For each case, the coefficients \( f_0, f_1, \) and \( f_2 \) can be calculated for a least squares best fit. The EDH is defined as the height at which \( dM / dz \) is equal to 0, or, equivalently, the height at which \( M \) is a minimum (Almond and Clarke 1983). As shown in Fig. 2, the difference between the modified refractivity \( M \) at height 0 and the modified refractivity \( M \) at the EDH is the EDS.
Observing AT, AP, and RH at different heights allows us to determine the vertical profile of the $M$, and thereby obtain the EDH and EDS. However, this method is only suitable for fixed positions due to the high cost and poor operability in the sea. For this reason, researchers have proposed evaporation duct model (EDM). The basic principle of the EDM is the Monin–Obukhov similarity theory. By measuring wind speed (WS), air temperature (AT), relative humidity (RH), and air pressure (AP) at a certain height and sea surface temperature (SST), an empirical model can be developed to calculate the vertical distribution of atmospheric refractivity and then obtain the evaporation duct parameters. Because of its convenient operation, this method has received extensive attention. Many EDMs have been proposed, such as Paulus–Jeske (PJ) (Jeske 1973), Babin–Young–Carton (BYC) (Babin et al. 1997), the fifth-generation mesoscale revise (MM5REV) (Jiao and Zhang 2015), Naval Postgraduate School (NPS) (Frederickson et al. 2000), Naval Warfare Assessment (NWA) (Liu and Blanc 1984), and based on Coupled Ocean–Atmosphere Response Experiment (COARE) (Fairall et al. 2003) models. The PJ model is the most successful and widely used EDM in the early. But the PJ model has some drawbacks. For example, the predicted result is generally higher than the actual height under unstable conditions. The BYC model generalizes the Monin–Obukhov similarity theory to very low WS conditions. (Godfrey and Beljaars 1991; LeMone et al. 2019). The Tropical Ocean and Global Atmosphere Coupled Ocean–Atmosphere Response Experiment calculation method was introduced into the NPS model, and the salinity was corrected at the same time. The MM5REV model is improved from the fifth-generation mesoscale model, focusing on the nearshore effect of evaporation ducts. The NWA model and the NPS model use different stability functions for WS and potential temperature. The COARE model is based on the COARE3.0 flux algorithm proposed in 2003. It uses a new roughness length parameterization methods and stability function to expand the applicable area to medium and high dimensions, and the WS is expanded from 12 to 20 m s$^{-1}$ (Yang et al. 2017; K. Zhang et al. 2016). Although the EDMs are all based on Monin–Obukhov similarity theory, the stability functions and roughness length parameterization are not the same, with each derived from meteorological (WS, AT, RH, and AP) and hydrological (SST) observational data obtained from different sea areas. This also indirectly causes the prediction results of the EDMs to be inconsistent in certain meteorological and hydrological environments (Tian et al. 2020).

To compare and verify the differences in prediction accuracy of these models in different environments, significant research on the applicability and sensitivity of the models has been conducted. In Yang et al. (2017), a study on the applicability of the PJ model and the NPS model was carried out in the South China Sea. The results show that the latter has higher prediction accuracy and obtained an average error in the EDH of $-1.7$ m. Cook (1991) analyzed the sensitivity of different EDMs and found the prediction results of the EDH to be consistent with the sensitivity of meteorological and hydrological parameters. Guo et al. (2019) use the percentage of
the difference between the predicted value and the reference value divided by the reference value to analyze the errors of the PJ model and the NPS model to predict EDH, and the results are 11.43% and 14.81%, respectively. Additionally, numerical simulation methods have been used to analyze the EDM under typhoon conditions in the northwest Pacific (Shi et al. 2019). Results show that the prediction accuracy of the EDM is different in different environments, which can be attributed to the different stability functions and roughness length parameterization. As such, the ability to determine the sensitivity of different models to input parameters that allows choosing a model with high prediction accuracy is worthy of study and exploration.

In addition, Sobol sensitivity analysis is intended to determine how much of the variability in model output is dependent upon each of the input parameters, either upon a single parameter or upon an interaction between different parameters (Sobol et al. 2011; Nossent et al. 2011). In this paper, it is used to quantify the contribution of input variables to the total variance of the EDH output results of each model, and analyze the impact of changes in the input parameters on the output results.

To improve the prediction accuracy of the evaporation duct, this paper analyzes the sensitivity of six commonly used EDMs (PJ, BYC, NPA, NWA, MM5REV, and COARE models) to meteorological and hydrological parameters, a model selection optimization method (MSOM) is proposed. For training and verification of this method numerical and observational datasets were used.

The layout of this paper is as follows. Section 2 presents the MSOM method and introduces the dataset; the MSOM is implemented by analyzing the sensitivity of the EDM to meteorological and hydrological parameters, and the optimal model for each group is obtained in section 3; section 4 uses the numerical simulation dataset and ocean observational dataset from the offshore observation tower located in the South China Sea to verify the MSOM. The conclusions and discussion are given in section 5.

2. Method and data

a. Method

The MSOM proposed on this paper consist of three parts, each one represented by a color in Fig. 3. In part 1 (blue line), the sensitivity of existing EDMs (PJ, BYC, NPA, NWA, MM5REV, and COARE model) to meteorological and hydrological parameters (WS, AT, RH, AP, and SST) is analyzed. The methods of analysis include sensor observation accuracy, curve graph, and Sobol indices. Then environmental parameters were grouped according to WS, RH and air–sea temperature difference (DT). In part 2 (green line), the reference EDH and the predicted EDH of each EDMs are obtained corresponding to each group of environmental data. In each group, analyze the average error of prediction values of different models, and then select the model with the smallest average error in prediction as the optimal model for the group. In part three (orange line), when a new item of observational data is obtained, first determine which group the observational data belongs to, and then select the optimal model corresponding to this group to obtain the EDH.

b. Data

In this paper, two dataset are used. The numerical simulation dataset is used to model the MSOM method. The numerical simulation data and ocean observational dataset are used to verify the MSOM.

1) NUMERICAL SIMULATION DATASET

European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis V5 (ERA5) data have been used as validation data (Hersbach et al. 2020). It was first released in January 2019. The data can be used for climate monitoring, numerical weather forecast, etc. To train and obtain the optimal model for the group that can cover as many groups as possible, a numerical simulation based on the AP, AT, RH, WS, and SST at different heights of the air–sea interface in the South China Sea throughout 2016 is used (shown in Fig. 4).

The attributes of numerical simulation are shown in Table 1. This paper uses the ERA5 data with a horizontal resolution of 12 km, a range of 5°–25°N, 105°–125°E, and a period of 1 January–31 December 2016. To more accurately obtain the reference value of the EDH, mesh refinement was carried out using the Weather Research and Forecasting (WRF) Model to obtain data of AP, AT, and RH with a
vertical resolution of 3 m and data of SST. To reduce the influence of land–sea exchange on the simulation results of the meteorological and hydrological parameters, this paper selects the numerical simulation data in the yellow area of Fig. 4 to train the MSOM.

2) OCEAN OBSERVATIONAL DATASET

The performance of the MSOM is verified in practical applications using ocean observational data. The offshore experimental platform (21°27′36.73″N, 111°19′24.02″E) of the China Meteorological Administration Bohai Ocean Meteorological Science Experimental Base is selected to acquire meteorological and hydrological data at a distance of 6.5 km from the coast in real time. The experimental period is from 30 June to 30 July 2019.

As shown in Fig. 5, the offshore observation platform deploys a total of 10 layers of sensors on the vertical gradient. The height between each layer is 3 m in 1–5 floors, and 4 m in 5–10 floors. Temperature and humidity sensors are installed on each floor. An additional infrared temperature sensor and wind sensor are installed on the first floor to measure the SST and WS, respectively. A barometric pressure sensor is installed on the fourth floor to measure the AP. The static pressure and water vapor pressure values of each layer are calculated through the relationship between the saturation vapor pressure, static pressure, and water vapor pressure (Buck 1981).

A total of 37,364 data points were obtained in the ocean experiment. The observational data of the WS, AT, RH, and AP on the second floor and the SST are used as the model input parameters. To obtain more accurate data, the absolute height of the second floor from the sea surface is corrected by using tidal observational data. The time series observational data are shown in Fig. 6. The missing data in the figure are caused by a power outage.

![Fig. 4. Numerical simulation area.](image)

![Fig. 5. Offshore experimental platform.](image)

![Fig. 6. Observed data from the offshore experimental platform.](image)

<table>
<thead>
<tr>
<th>Attribute</th>
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<tr>
<td>Range</td>
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<td>Horizontal resolution</td>
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<td>WSM 6-class graupel scheme</td>
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<td>RRTMG</td>
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<td>Surface layer scheme</td>
<td>Revised MM5</td>
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<td>Land surface plan</td>
<td>Unified Noah</td>
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<td>Boundary layer scheme</td>
<td>YSU</td>
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<tr>
<td>Cumulus layer scheme</td>
<td>Kain–Fritsch</td>
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</table>
3. Implementation

a. Sensitivity analysis of the EDM

The difference between the stability functions and roughness length parameterization methods determines that the EDMs have different accuracy under different conditions of meteorological and hydrological parameters. The degree of change of meteorological and hydrological parameters has different effects on the EDH predicted by EDM. That is, EDMs have different sensitivities to different parameters.

This section conducts sensitivity analysis from three aspects of sensor observation accuracy, curve graph, and Sobol indices. According to the conclusion of sensitivity analysis, the multi-dimensional space constructed by the meteorological and hydrological parameters is grouped, which provides the basis for get the optimal model for each group.

1) SENSOR OBSERVATION ACCURACY

The input parameters of the EDM are the meteorological and hydrological values measured by the sensors, including the WS, AT, RH, AP, and SST. In actual ocean observations, under the same environmental conditions, the EDH deviation output by the EDM has different sensitivity to the sensor accuracy of different parameters. This section analyzes the influence of different meteorological and hydrological parameters on the prediction accuracy of the evaporation duct model in actual ocean observations.

In this section, the Monte Carlo simulation method is used. The sensor observation accuracy is regarded as the random

<table>
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<td>AT</td>
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<td>±0.2°C</td>
</tr>
<tr>
<td>RH</td>
<td>HMP155</td>
<td>30% to 100%</td>
<td>±5%</td>
</tr>
<tr>
<td>WS</td>
<td>WS425</td>
<td>0 to 35 m s⁻¹</td>
<td>±0.3 m s⁻¹</td>
</tr>
<tr>
<td>AP</td>
<td>PTB220</td>
<td>900 to 1100 hPa</td>
<td>±0.5 hPa</td>
</tr>
<tr>
<td>SST</td>
<td>SI-111</td>
<td>−5° to 30°C</td>
<td>±0.2°C</td>
</tr>
</tbody>
</table>

FIG. 7. EDH scatterplot. The x axis is the EDH calculated by setting parameters, and the y axis is the EDH calculated after adding random errors.
The mean absolute error (MAE) of the EDH is calculated based on the Monte Carlo simulation data, and the sensitivity of each model to the sensor observation accuracy is analyzed. MAE = \( K^{-1} \sum_{i=1}^{K} |h'_i - h_j| \), where \( K \) is the data size, and \( h_i \) and \( h'_i \) represent the EDHs obtained from the original observational data and by adding random errors, respectively. The results are shown in Fig. 8. The observation accuracy of the RH sensor has the most significant impact on each model. The AP has almost no effect on the prediction results of all models. The accuracy has a relatively smaller impact on each model.

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2) CURVE GRAPH SENSITIVITY ANALYSIS

Through the analysis of the sensitivity to the sensor observation accuracy, it can be seen that WS and RH are important factors affecting the EDM, while AP is the opposite. Therefore, we use the curve graph in this section to focus on analyzing the sensitivity of the EDM to WS and RH. At the same time, the DT is an important factor affecting the atmospheric conditions, and the change of the atmospheric conditions has a direct impact on the evaporative duct (Paulus 1985). So by setting change intervals of WS, RH, and DT, the EDH of each model is calculated and the curve is drawn. Then the sensitivity of the model is analyzed under the combination of different input parameter intervals. Specifically, different models have different methods for determining the atmospheric stability. For a unified description, the most commonly used method for determining the atmospheric stability by the DT is adopted in this paper. A DT value that is close to 0°C indicates that the atmospheric stability is close to a neutral condition. A DT value less than 0°C indicates atmospheric is under unstable conditions. In all other cases, it is under stable conditions (Zhang et al. 2016a).

(i) RH and DT

Figure 9 shows the EDH curve of each model under different combined conditions of RH and DT. For RH between 50% and 100%, and, DT between -5° and 5°C, the WS is 4.3 m s\(^{-1}\), the AP is 1000 hPa, the observation height is 6 m, and the EDH is no greater than 40 m.

The PJ model has a significantly different sensitivity from other models due to the correction of the EDH when DT is greater than -1°C (Paulus 1985). Under stable conditions, the EDH was suppressed. At the same time, it can be seen from Fig. 9 that under stable conditions of high RH, the EDH predicted by the EDM other than PJ model usually has a large number of cases of 0 m, but this usually does not match the actual results. The PJ model is improved to address this problem. When the DT is equal to 0°C, the EDH is greater than that when the DT is -1°C, and the calculation result is the result at -1°C.

The other models have similar sensitivity. Under stable conditions, the EDH values increase rapidly. At this time, the models except for PJ model also are most sensitive to the DT. Under unstable conditions and a low RH, as the DT decreases, the EDH from the BYC, MM5REV, and COARE models first decreases and then increases. However, other models only show this trend when the RH is high. The fundamental reason for this trend is that BYC, MM5REV, and COARE models use the same stability functions under unstable conditions (Fairall et al. 1996).

(ii) RH and WS

Figure 10 shows the EDH curves of each model under different combined conditions of RH (between 50% and 100%) and WS (between 0 and 20 m s\(^{-1}\)). DT is -2°C, AP is 1000 hPa, and observation height is 6 m.

From Fig. 10, it can be seen that the models are consistent in the predicted trends of the EDH. The EDH is low when the RH is high and the WS is low. Compared with other models, the EDH of the PJ model is higher under a low RH and high WS environment. Under unstable conditions, the BYC, MM5REV, and COARE models show the same sensitivity due to the adoption of the same stability functions. Under a low WS environment (less than 5 m s\(^{-1}\)), a “buffer” in the EDH falling speed exists, which makes the EDH relatively higher than other models under the same conditions.
Figure 11 shows the EDH curve of each model under different combined conditions of WS (between 0 and 20 m s\(^{-1}\)) and DT (between \(-5^\circ\) and \(5^\circ\)) with an RH of 80% and AP of 1000 hPa.

Under unstable conditions, the EDH output by each model has basically the same variation tendency with WS and DT. The models show no sensitivity to the DT in the low WS environment. However, as the WS increases, the sensitivity of each model to the DT increases.

Under stable conditions, the sensitivity of the PJ model is different from that of the other models. The change of the EDH is only related to the WS and has nothing to do with the DT. Aside from the PJ model, other models show the value of the EDH to be more sensitive to the WS when in a low WS environment. The EDH rises rapidly as the WS decreases. In comparison, the increase in the EDH predicted by the COARE model is weaker than that of other models. It should be noted that as the wind speed increases, the EDH becomes more and more sensitive to DT.

The following conclusions can be drawn from this section:

1) Under unstable conditions, the EDH obtained by each model will decrease with the increase of RH and with the decrease of WS. In comparison, EDH is not sensitive to the DT.
2) Under stable conditions, all models aside from the PJ model are more sensitive to the WS under low WS conditions and are otherwise more sensitive to the DT.

3) SOBOL SENSITIVITY ANALYSIS

This paper attempts to use the total-order Sobol indices (ST) to analyze the sensitivity of each model to input parameters. Therefore, the value range of each input parameter is set according to the sensor observation range. The value range is discretized according to Table 3, and different input parameter combinations are constructed. Each input parameter is sequentially input into each EDM according to the discrete value point, and the ST of the input parameter to different models are then calculated.

The results are shown in Fig. 12. The gray points represent values of the ST, while the red line corresponds to the median value of the ST in each interval. It can be concluded that the sensitivity of different models to the WS shows similar characteristics and is negatively correlated with the ST. The model shows high sensitivity when the WS is less than 4 m s\(^{-1}\), with the ST exceeding 0.5 (approaching 1). This means that small changes in the WS will cause large significant changes in the EDH. In comparison, the ST in the WS ranges of 4–12 and 12–20 m s\(^{-1}\) are about 0.3 and close to 0, respectively. This shows that as the WS increases, the EDM output tends to stabilize.
On the contrary, the RH is proportional to the ST. When the RH ranges from 70% to 100%, 50% to 60%, and others, the ST is higher than 0.5, about 0.3, and less than 0.3, respectively. Compared with the WS, the ST and RH change gradually in each interval.

In addition, the ST of the models (except for the PJ model) to DT is significantly related to the atmospheric stability. The ST is usually lower than 0.3 in unstable conditions and higher than 0.3 in stable conditions (sometimes exceeding 0.5). It can be seen from the above analysis that the conclusion of the influence of input parameters on the EDM is consistent with that of curve graph sensitivity analysis.

b. Grouped observational parameters

To select the EDM with higher prediction accuracy under the conditions of different combinations of the input parameters, the three input parameters (WS, RH, and DT) that most
significantly affect the accuracy of the EDH are divided into different intervals according to the ST. The more sensitive the output of the model is to the input parameters means that the change of the input parameters has a greater impact on the output of the model. Therefore, the principle of interval division is to split the sensitive interval or otherwise integrate.

The ST statistical results of each model in each interval of the input parameters are shown in Fig. 13. According to the analysis results of the ST, the largest ST of each input parameter for each model in the same interval is used as the judgment basis for interval division. If the value is greater than 0.5, the interval is divided. If the value is less than 0.3 in adjacent intervals, the intervals are integrated; otherwise, it remains unchanged.

According to the above interval division rules, the WS, RH, and DT are divided into 6, 8, and 10 intervals, respectively. That is, the model input parameters are constructed into 6×8×10 = 480 groups. To facilitate the understanding, the number of each group is defined as the combination of the parameter name and interval number as listed in Table 4.

### c. Optimal model

To train and obtain the optimal model M\textsubscript{opt} for each group that can cover as many groups as possible, a numerical simulation based on the ERA5 dataset is used. Figure 14 is a histogram of the WS, RH, DT, and EDH values obtained by numerical simulation, covering most of the group of Table 4.

According to Table 4, the numerical simulation data are grouped. As shown in Figs. 15a and 15b show the grouping under stable and unstable conditions. Each group includes the mean of the prediction deviations of the six models in that group. The numbers in the first three rows of the x axis are the interval numbers of WS, DT, and RH, which correspond to the interval numbers in Table 4. The fourth row of the x axis is the number of the model with the minimum average deviation (MAD) in the group, and the relationship between the number and the model is as described in the legend. Through the analysis of Fig. 15, we obtained the optimal model M\textsubscript{opt} for each group.
4. Results

a. Validation of numerical simulation dataset

The MSOM is validated using the numerical simulation dataset. The average errors of the MSOM and the EDMs are shown in Fig. 16. Regardless of being under stable or unstable conditions, there are more regions where the deviation of MSOM’s prediction results is close to 0. In addition, the prediction results under unstable conditions are better than those under stable conditions. On one hand, it is difficult for the model to find a perfect stability universal function to meet the demand for obtaining high-precision prediction results under stable conditions; on the other hand, the slope of the modified atmospheric refractive profile is large (almost a vertical straight line), and large errors will be introduced when calculating the EDH under stable conditions.

According to Eq. (3), the relative errors \( \delta_j \) of the EDH for each model are obtained:

\[
\delta_j = \frac{|h_{\text{pre}}^k - h_{\text{ref}}^k|}{h_{\text{ref}}^k} \times 100\%,
\]

where \( j \) is the model number, \( h_{\text{pre}}^k \) represents the EDH obtained by the \( j \)th model using the \( k \)th item observational data, and \( h_{\text{ref}}^k \) represents the reference value of the EDH corresponding to the \( k \)th item observational data.

The results shows that, under stable conditions, the relative errors of the PJ, BYC, MM5REV, NPS, NWA, COARE, and MSOM are 34.6%, 25.7%, 25.5%, 25.5%, 24.5%, 25.5%, and 19.5%, respectively. The PJ model has a larger relative error than other models. What is more, the relative error of MSOM is reduced by 15.1% compared with the PJ model. Under unstable conditions, the relative errors of the models are 20.5%, 19.2%, 18.0%, 17.3%, 16.6%, 18.0%, and 14.9%, respectively. The relative error of PJ model is still the largest. The relative error of MSOM is reduced by 5.6% compared to the PJ model.

b. Validation of ocean observational dataset

The WS, RH, DT, and EDH distribution of ocean observational dataset are shown in Fig. 18. It is slightly different from the distribution of the numerical simulation dataset shown in Fig. 14. However, the distribution range of the observational data is a subset of the numerical simulation dataset.

According to Eqs. (1) and (2), the \( M \) value at different heights and vertical profiles are obtained, and then the height corresponding to \( \partial M/\partial z = 0 \) is the reference value of the EDH. Figure 19 shows the observed \( M \) value and the fitted \( M \) profile at the height of each floor, as well as the \( M \) profile and EDH calculated by each model. It can be seen that the results predicted by different models deviate from the reference value.

The results shows that, under stable conditions, the relative errors of the PJ, BYC, MM5REV, NPS, NWA, COARE, and MSOM are 17.8%, 20.7%, 23.3%, 23.1%, 21.9%, 21.0%, and 12.6%, respectively. Under unstable conditions, the relative errors are 20.6%, 18.4%, 19.1%, 19.1%, 19.8%, 19.1%, and 13.5%, respectively. The relative error of the MSOM is reduced

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<table>
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<th>Interval</th>
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<th>( H ) (%)</th>
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<td>[50, 60)</td>
<td>[−5, −1)</td>
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<td>3</td>
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<td>10</td>
<td>—</td>
<td>—</td>
<td>[4, 5]</td>
</tr>
</tbody>
</table>

FIG. 13. ST statistical results of each input parameter for each model in the same interval.

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Table 4. Environmental division.

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The results shows that, under stable conditions, the relative errors of the PJ, BYC, MM5REV, NPS, NWA, COARE, and MSOM are 17.8%, 20.7%, 23.3%, 23.1%, 21.9%, 21.0%, and 12.6%, respectively. Under unstable conditions, the relative errors are 20.6%, 18.4%, 19.1%, 19.1%, 19.8%, 19.1%, and 13.5%, respectively. The relative error of the MSOM is reduced...
by a maximum of 10.7% and 7.1% under stable and unstable conditions, respectively.

As shown in Fig. 20, under stable conditions, the prediction error medians of PJ, BYC, MM5REV, NPS, NWA, COARE, and MSOM are 0.3, 0.7, 0.9, 0.9, 1.0, 0.2, and 0.1 m, respectively. Under unstable conditions, the prediction error medians are 0.7, −0.3, −0.4, −0.4, −0.1, −0.4, and 0.1 m, respectively. It can be seen that the prediction error of the MSOM is closer to 0 m.

Fig. 14. Histogram of the (a) WS, (b) RH, (c) DT, and (d) EDH values obtained by numerical simulation.

Fig. 15. Grouping and optimal models under (a) stable and (b) unstable conditions.
Meanwhile, its quartiles and margins of the upper and lower quartiles are closer to 0 m. Under stable and unstable conditions, the prediction error medians of the MSOM are reduced by 0.8 and 0.6 m, respectively. The prediction accuracy of the MSOM is better than other models.

The time-varying characteristic of the EDH is also a benchmark for the performance of each EDM. Therefore, with “hour” and “day” as the time scales, the time and daily average changes of model prediction errors are analyzed. The results are shown in Fig. 21. On the “hour” scale, the model prediction relative errors change slightly. However, it can be seen that the EDH deviation is caused by the different stability functions during the alternate change of the atmospheric stable conditions. On the “day” scale, the model prediction relative errors fluctuate greatly. The EDMs based on the Monin–Obukhov similarity theory have a consistent trend when predicting the EDH, but there are still differences in the prediction values of the EDH. In any case, the relative error of the MSOM is better than other models.

5. Conclusions and discussion

Existing EDMs are all based on parameterized methods of the marine atmospheric boundary layer, which requires the meteorological and hydrological parameters as inputs. The fundamental difference between different parameterized methods is the difference between the stability functions and roughness length parameterization, which are often derived from observational data at different times and in different regions. Therefore, the EDMs based on the bulk parameterized method have various precisions under different environmental conditions. This also means that in a multidimensional environment space composed of meteorological and hydrological parameters, the prediction accuracy of each EDM is different. In actual application scenarios, how to select a model that has
prediction results closer to the reference value from multiple EDMs remains a challenge.

This paper makes a qualitative and quantitative analysis of the EDM to the input parameters from simple to complex in three aspects: sensor observation accuracy, curve graph, and Sobol sensitivity analysis. Through the qualitative analysis of the sensor observation accuracy and the curve graph, it can be seen that each model has different sensitivities to different intervals of the input parameters. Changes in the WS, RH, and DT will all affect the EDH output by the EDM, while changes in AP have almost no effect. Under unstable conditions, the EDH output by each model will decrease with the increase of RH or decrease of WS. Through Sobol sensitivity to quantitatively analyze the sensitivity of each model in a multidimensional environment space, the rules and results of the interval division of meteorological and hydrological parameters are given. Numerical simulation methods are used to simulate the meteorological and hydrological parameters in different seasons and areas in the South China Sea. The model selection optimization method (MSOM) is proposed by those simulated data.

This paper also uses ocean observation data to verify the prediction accuracy of the MSOM. Meteorological observation data at different heights and SST on the South China Sea offshore experimental platform are obtained, and then the M profile is fitted to obtain the reference value of the EDH. The prediction relative error of the MSOM is smaller than the other EDMs, no matter condition (stable or unstable). At the
same time, the prediction accuracy of the MSOM is improved compared with the existing EDMs in different time scales (“day” and “hour”), which has reached the research purpose of this paper.

This paper uses the reanalysis dataset to drive the mesoscale atmospheric numerical model to obtain the reference value of the EDH. The reanalysis dataset is based on advanced satellite remote sensing technology and assimilation technology, resulting in greatly improved temporal and spatial resolution and accuracy. However, it still cannot completely replace the actual ocean observation data. Therefore, it is inevitable that there are deviations in varying degrees between the reference value and the actual observed values of the EDH. To further reduce the deviation, we plan to use more ships and buoys to obtain more accurate observational data in future work to correct the deviation of the reference values obtained by the numerical simulation and optimize and verify the MSOM in more sea areas.

The MSOM proposed in this paper is based on existing models and is an optimal method for existing models under current environmental conditions. Because the stability functions and roughness length parameterization methods of the existing models are not perfect, even the prediction results of the model with the smallest prediction relative error deviate from the reference value of the EDH. As a result, there is still potential for improving the MSOM. Therefore, in future work, we will try to use more methods such as deep learning, ensemble prediction, and data fusion.

![Boxplot of each model's prediction error under (a) stable and (b) unstable conditions.](image)

**FIG. 20.** Boxplot of each model’s prediction error under (a) stable and (b) unstable conditions.

![Prediction relative error of each model on (left) “hour” and (right) “day” scales.](image)

**FIG. 21.** Prediction relative error of each model on (left) “hour” and (right) “day” scales.
based on observation data to obtain higher-precision evaporation duct parameters.

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Data availability statement. The ERA5 data used in this study can be retrieved from the following website: https://confluence.ecmwf.int/display/CKB/How+to+download+ERA5. Ocean observational data will be available upon request to the corresponding author.

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