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An Improved MG Model for Turbulent Mixing Parameterization in the Northwestern South China Sea

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Abstract: Using in situ microstructure observations from 2010 to 2018, this study assesses the applicability of turbulent mixing parameterization schemes in the northwestern South China Sea (NSCS) and improves the MG model proposed by MacKinnon and Gregg in 2003 using machine learning methods. The results show that the estimation error of the MG model is still more than one order of magnitude in the NSCS. Also, the importance of parameters obtained from machine learning indicates that the normalized depth (D) is one of the most relevant parameters to the turbulent kinetic energy dissipation rate ε . Therefore, in this study, D is introduced into the MG model to obtain an improved MG model (IMG). The IMG model has an average correlation (r) between the estimated and observed $\log_{10}\varepsilon$ of 0.79, which is at least 49% higher than the MG model, and an average root mean square error (RMSE) of 0.25, which is at least 42% lower than that of the MG model. The IMG model accurately estimates the multi-year turbulent mixing observed in the NSCS, including before and after tropical cyclone passages. This provides a new perspective to study the physical principles and spatial and temporal distribution of turbulent mixing.

Keywords: turbulent mixing parameterization; MG model; northwestern South China Sea; machine learning



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1. Introduction

Turbulent mixing is a vital process for the redistribution of nutrients, sediments, freshwater, and pollutants throughout the water column [1]. Consequently, parameterizing turbulent mixing represents a pivotal topic in physical oceanography. However, this endeavor is beset with challenges. Firstly, turbulent mixing occurs at an exceedingly small scale, in the order of microns, which most ocean models are unable to resolve. Secondly, direct long-term and large-scale measurements of turbulent mixing are exceedingly difficult to obtain. Therefore, the development of mixing parameterization has become the most viable approach.

Previous investigators have proposed various parameterization schemes for the ocean turbulent kinetic energy dissipation rate ε [2–5]. The widely used schemes include those provided by Mellor and Yamada [6], Pacanowski and Philander [7], Chen et al. [8], and the K-profile parameterization [9]. In recent decades, there has been a growing focus on

the enhancement of internal mixing caused by the breaking of internal waves [10–12]. Based on the wave–wave interaction and wave energy transfer theories, parameterization schemes based on fine-scale observations were developed, such as the GH model [13], K06 model [14], and MG model (proposed by MacKinnon and Gregg in 2003) [15]. Moreover, the Thorpe scale method, which is based on the turbulent eddy overturning scale and buoyancy frequency, has also been proposed [16,17]. All these parameterization schemes are based on parameters associated with water density and current velocity. These developments have benefited ocean modeling and prediction, although uncertainties remain a significant challenge [18,19]. The booming development of machine learning has brought us new ways to study turbulent mixing [20–22]. However, the inability of machine learning to provide display expressions has thus far hindered further development in this direction. Further study is required to determine how machine learning can be used to enhance existing parameterization schemes.

The northwestern South China Sea (NSCS) exhibits a considerable diversity of bathymetric and oceanographic conditions. It has long been regarded as a focal point for dynamic research endeavors [11,23,24]. Given the challenges associated with obtaining microstructure measurements, the Thorpe scale method is frequently employed to estimate overturns [10,25,26]. In addition, different fine-scale parameterizations are often used to estimate diapycnal diffusivity $K\rho$. For example, based on the Gregg–Henyey–Polzin scale [14,27], Yang et al. [28] provided a three-dimensional distribution of turbulent mixing in the South China Sea (SCS), and Sun et al. [29] reported seasonal variations in deep water turbulent mixing in the NSCS. Lu et al. [30] conducted microstructure measurements in the northern continental shelf and deep-water areas of the South China Sea, deriving two different parameterizations using the Richardson number (Ri). However, the applicability of the fine-scale parameterization in the SCS has only been tested in a few studies. Recently, Shang et al. [31] and Liang et al. [32] investigated the applicability of the GH model and the MG model in the SCS and suggested that the MG model is more suitable for the SCS. Numerous studies have highlighted the superior applicability of the MG model in the NSCS compared to other parameterization schemes [31,33,34]. However, the error between the MG model estimates and the observed data is still more than one order of magnitude, especially in the mixed layer. One reason for this is the uncertainty in ε_0 . While theoretically, this constant should be consistent with the background values of the oceans, empirical evidence suggests that ε_0 can vary based on observed data. This variability poses challenges in applying the scheme to research when observational data are lacking. Consequently, these limitations have led to caution in the study of turbulent mixing in the NSCS, highlighting the urgent need for a swift and rational turbulent mixing parameterization scheme tailored to this specific area.

Using in situ microstructure observations from 2010 to 2018, this study evaluates the applicability of turbulent mixing parameterization schemes and improves the MG model with machine learning methods in NSCS. The rest of the paper is organized as follows. Section 2 provides a detailed introduction to the hydrological data and methods. Sections 3 and 4 present the applicability of traditional parameterization schemes and introduce new parameterization schemes, respectively. Sections 5 and 6 present the discussions and conclusions, respectively.

2. Observations and Methods

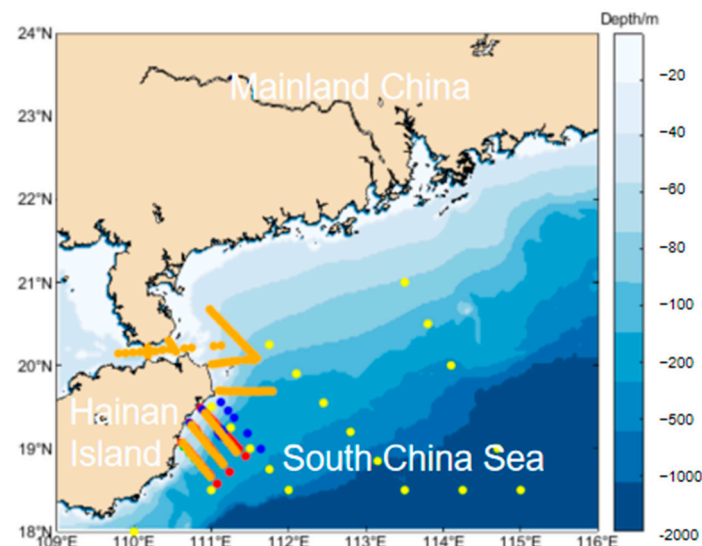
2.1. Observations

Observational data were collected from 2010 to 2018, including 261 CTD profiles, 261 ADCP profiles, 94 TurboMAP profiles, and 143 MSS90 profiles. Observation periods ranged from February to July, with a concentration in July, as listed in Table 1.

Table 1. Dataset information, including the cruise number, year, month, and profile numbers of CTD, ADCP, TurboMAP, and MSS90.

Cruise Number	Year	Month	CTD	ADCP	TurboMAP	MSS90
1	2010	April–May	19	19	19	—
2	2012	February	28	28	28	—
3	2012	July	47	47	47	—
4	2016	July	40	40	—	35
5	2018	July	127	127	—	108
Total			261	261	237	

In this study, the observed hydrological parameters include temperature (T_e), salinity (S_a), density (ρ), water depth (H), horizontal velocity (U), stratification (N), shear (S), and dissipation rate (ϵ). The observation stations used in this study must include N , S , H , and ϵ , with a total of 237 qualified stations. Figure 1 shows that the qualified stations covered the entire NSCS. Detailed information on the data used in this study can be found in Li et al. [34] and Shang et al. [31].

**Figure 1.** Topographic map of the northwestern South China Sea, along with all the stations collected from 2010 to 2018. Yellow, green, red, blue, and orange indicate April–May 2010, February 2012, July 2012, July 2016, and July 2018, respectively. Topography data are from <https://www.ncei.noaa.gov/products/etopo-global-relief-model> (accessed on 27 December 2024).

2.2. MG Model

Parameterizations are applied to estimate turbulent dissipation using fine-scale parameters (e.g., N and S), which are more commonly measured than microstructure. The MG model is the most commonly used and practical analytical model in the NSCS [31,33]. This is because the low-mode shear in our study area mainly came from low-frequency internal waves, such as diurnal and semidiurnal waves [33,34], which was similar to features of the internal wave field over the New England Shelf, where the MG model was derived initially [15]. It is given by

$$\epsilon_{MG} = \epsilon_0 \left(\frac{N}{N_0} \right) \left(\frac{S}{S_0} \right) \quad (1)$$

where the choice of S_0 and N_0 refers to the studies by Li et al. [33] and Sun et al. [34]. Here, we choose $S_0 = N_0 = 5.1 \times 10^{-3}$ rad/s. ϵ_0 is an adjustable constant that gives the model dissipation rate the same cruise average as the observed data. The adjustable constant ϵ_0

shows great variability in different regions and seasons, spanning from 10^{-10} to more than 10^{-8} W kg $^{-1}$ [35–38]. This regional and temporal variability of ε_0 strongly suggests the importance of different physical processes for the setup and maintenance of the background levels of turbulent dissipation.

2.3. Parameter Importance

In recent years, machine learning has gradually developed and gained popularity in the field of oceanography [20,21,39]. However, machine learning models have high complexity and low interpretability. This hinders the further development of oceanography. Therefore, it is still necessary for us to try to understand machine learning models as much as possible, which is conducive to our understanding of the physical essence behind them. Many researchers have proposed many methods to explain machine learning models, and the parameter importance is the most important method. The most commonly used methods for calculating parameter importance include the Gini index [40], permutation [41], and SHAP values [42].

The Gini index can be calculated based on the random forest model (RF), which is the most commonly used model in machine learning. The idea of evaluating parameter importance using the Gini index is to sort by the contribution of each parameter on each tree in the random forest. The permutation is to shuffle the i -th parameter of the n samples when calculating the importance of the i -th parameter. If a parameter is associated with the target variable, shuffling the order will affect the error, and the stronger the association, the greater the impact. SHAP is a method based on the Shapley value theory, which is used to interpret the prediction results of machine learning models. It provides global and local interpretability for the model by decomposing the predicted results into the influence of each parameter.

3. Applicability of MG Model in the NSCS

The MG model in the NSCS is evaluated in this section. Different ε_0 values are selected for the parameterizations due to their different mixing backgrounds: for April–May 2010, $\varepsilon_0 = 1.65 \times 10^{-9}$ W kg $^{-1}$; for February 2012, $\varepsilon_0 = 5.2 \times 10^{-8}$ W kg $^{-1}$; for July 2012, $\varepsilon_0 = 1.65 \times 10^{-10}$ W kg $^{-1}$; for July 2016, $\varepsilon_0 = 0.96 \times 10^{-9}$ W kg $^{-1}$; for July 2018, $\varepsilon_0 = 8.52 \times 10^{-8}$ W kg $^{-1}$. Figure 2 shows the distribution of dissipation rates in N^2 and S^2 spaces (observation and modeling). Dissipation rates in the NSCS (a–e) generally increase with increasing S^2 , and the MG model can roughly reflect this kinematic relationship. The dissipation rate from the MG model (f–j) exhibits a qualitatively consistent pattern with the observed data (a–e). However, the MG model underestimates the observed high dissipation rates, such as in 2010, 2016, and 2018. Turbulent mixing in the real ocean is quite complex and occasionally exhibits some extremely strong mixing, making it difficult for MG models to estimate accurately.

The dissipation rate profile observed in February 2012 and the dissipation rate profile estimated by the MG model are shown in Figure 3a,b. The horizontal axis represents the station number. It can be clearly found that the MG model (Figure 3b) underestimated the dissipation rate in the mixed layer. The local extreme values in the observations are not well estimated by the MG model. Depth averages of the dissipation rates estimated by the MG model are compared with the observations for February 2012, shown in Figure 3c. Estimates for other years are shown in Figures S1–S4. The observed dissipation rate sharply decreases from the mixed layer to the density interface (10–20 m below the surface), then slightly decreases with depth. Due to the limitations of the ADCP sampling range, the estimated depths of the MG model are mainly concentrated below 10 m. The MG model shows a general decreasing trend, which is consistent with the observed dissipation rate.

However, the MG model significantly overestimates or underestimates the value of the dissipation rate at the top or bottom by more than one order of magnitude. Then, the applicability of the MG model is quantified through statistical analysis. Table 2 lists the correlation coefficients (r) and root mean square errors (RMSE) between the observed and estimated $\log_{10}\epsilon$ for the MG model in depth averaging. The MG model has good performance in estimating dissipation rate, r is greater than 0.39, and RMSE is less than 0.51. Upwelling formed offshore of east Hainan Island, especially in July 2012. The r of the MG model is 0.46, indicating that the MG model can capture the ϵ and is less affected by upwelling. In the July 2018 observations, the MG model has an r of 0.39, which is the worst result compared to other cruise observations, possibly due to the wide distribution of measurement stations, including the Qiongzhou Strait. Considering the overall performance of predicting the dissipation rate, the MG model is indeed relatively suitable for the study area. Frequency internal wave mixing can explain why the MG model estimates have smaller biases but perform poorly in density interfaces. Previous studies have also shown that the microstructure observations of dissipation rates in shelf regions are robust with the MG model [31,33,34]. However, caution should be exercised when applying MG in areas with complex physical environments, and further modifications to the model may be necessary.

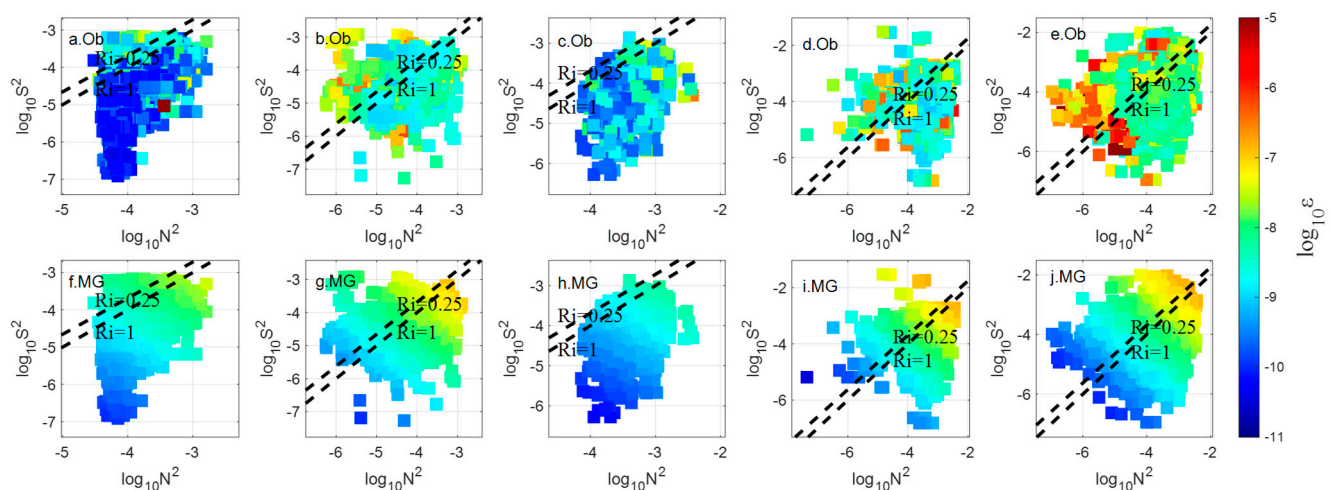


Figure 2. Comparison between dissipation parameterization and in situ observations. A base-10 logarithmic scale is used for dissipation data. (a,f) Results for April–May 2010, (b,g) results for February 2012, (c,h) results for July 2012, (d,i) results for July 2016, and (e,j) results for July 2018. The boundaries of $Ri = 0.25$ and $Ri = 1$ are shown for reference.

Table 2. The r and RMSE between the $\log_{10}\epsilon$ estimated by MG model and the $\log_{10}\epsilon$ observed for five cruise observations.

Model	April–May (2010)		February (2012)		July (2012)		July (2016)		July (2018)	
	r	RMSE	r	RMSE	r	RMSE	r	RMSE	r	RMSE
MG	0.63	0.49	0.46	0.43	0.49	0.45	0.68	0.51	0.39	0.25

The MG model, as a continental shelf model, has been validated in shelf seas such as the Celtic Sea [36], the Baltic Sea [37], and the New England continental shelf [15]. Our observations confirm that the MG model can also be applied in the NSCS, although with significant errors in the upper and bottom layers. The challenge in applying the MG model lies in the local adjustment of ϵ_0 . It has been shown that for different regions, the range of ϵ_0 varies from 10^{-10} W kg $^{-1}$ to above 10^{-8} W kg $^{-1}$. Even in the same regions, ϵ_0 can vary

by a factor of 2 according to seasonal changes [15,35]. Nevertheless, the MG model predicts the average characteristics of turbulence, providing researchers with a potentially useful tool if ε_0 can be appropriately estimated.

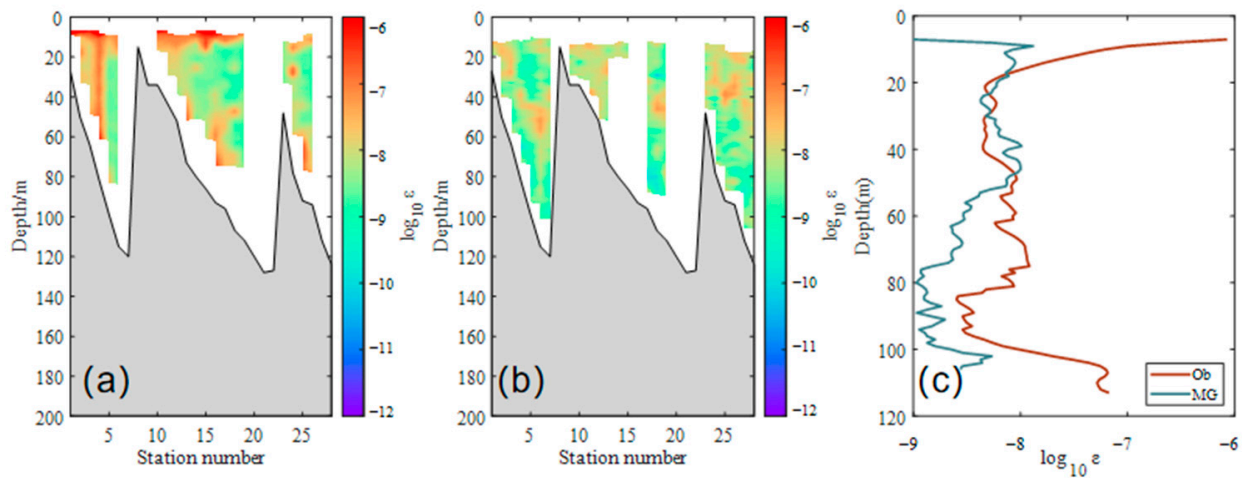


Figure 3. The dissipation rate profile observed in Feb 2012 and the dissipation rate profile estimated by MG model. (a) Dissipation rate profile observed. (b) Dissipation rate profile estimated by MG model. (c) Dissipation rates estimated and observed at depth average.

4. Improvement of the MG Model

4.1. Importance of D

According to potential impact factors proposed in earlier studies [20], we select six parameters that may affect the turbulent dissipation rate: Ri , shear (S), stratification (N), density (ρ), horizontal velocity (U), and normalized depth (D). Random forest [40] is used in this subsection, with 70% of the samples as the training set and the remaining 30% as the test set. We input these six parameters into the RF model and output the corresponding dissipation rate ε . The importance of the parameters is also calculated based on the Gini index, permutation, and SHAP values. Their calculation flow charts are shown in Figure 4. Figure 5 shows the sorted parameter importance, with all three methods consistently showing that ρ , D , and U contribute the most to the prediction of ε while N^2 , S^2 , and Ri contribute the least. The interpretation from the data view is that the dissipation rate is strongly correlated with D , ρ , or U . The physical explanation is that these depth-related parameters can better represent the effect of wind or bottom friction on mixing. Therefore, in the machine learning-based prediction of ε , depth-related parameters play a crucial role. Among them, D is easier to measure than ρ or U and can also directly represent the influence of external factors, such as wind and bottom friction. Based on the above considerations, we choose D to introduce the MG model.

The shortcomings of the MG model are still evident, and we attempt to make improvements within the framework of the MG model. The MG model believes that ε_0 is determined by the observed dissipation rate, which greatly reduces the applicability of the MG model. Therefore, we modify the MG model by parameterizing M . The M is given by:

$$M = \frac{\varepsilon_0}{N_0 \times S_0} \quad (2)$$

Based on the parameter importance indicated by machine learning, D has been shown to have a strong relationship with the dissipation rate. This is evident, and according to previous reports, active bottom mixing is caused by the interaction among internal waves, near-bottom currents, and rough topography [43–45]. Numerous ocean mixing

studies have illustrated that $K\rho$ generally decays from the bottom upward in the deep sea [14,43,46–48] and on the continental slope [49,50]. Several parameterization schemes have been proposed so that numerical models can incorporate various changes in ocean processes, from small-scale contributions to large-scale ocean processes [5,46,51,52]. These available turbulent mixing schemes are dependent on the distance from the seafloor. Hence, the inclusion of D in the parameterization formula is justified.

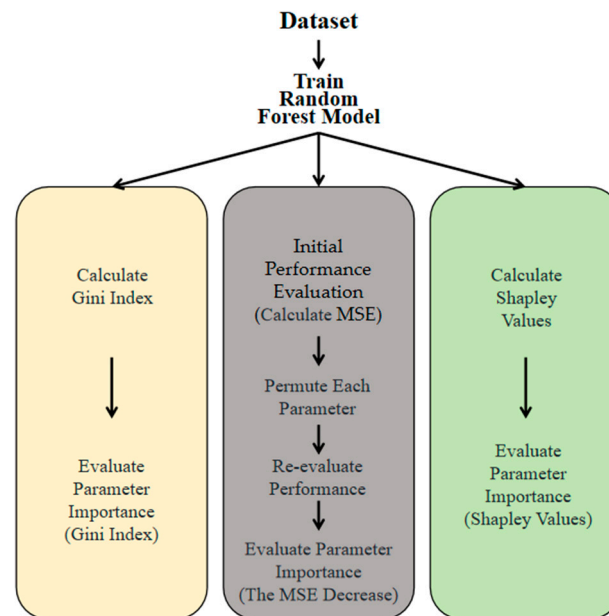


Figure 4. The calculation flow charts of the Gini index, permutation, and SHAP values.

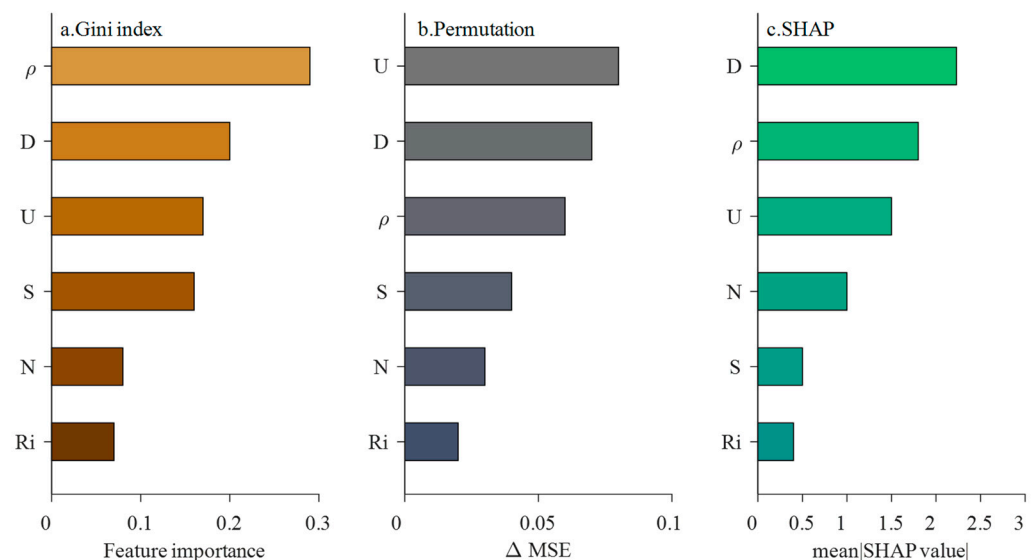


Figure 5. Parameter importance based on the Gini index, permutation, and SHAP values.

The primary sources of energy for ocean mixing are wind, surface buoyancy flux, and internal tides. Turbulent mixing in the upper mixed layer is primarily triggered by surface wind stress and surface buoyancy flux, while turbulent mixing below the upper mixed layer is generated by near-inertial motions and internal tides [53]. Therefore, the parameterization formula is written in the following form:

$$\varepsilon = \begin{cases} f(N, S, D), \text{upper mixed layer} \\ f(N, S, D), \text{stratified layer} \\ f(N, S, D), \text{bottom mixed layer} \end{cases} \quad (3)$$

Previous studies have found that the intensity of turbulent mixing decays from top to bottom. However, the intensity of turbulent mixing significantly increases near the seafloor. We evaluate the role of the parameter D in the NSCS. Figure 6 shows the relationship between D and ε in five cruise observations. It is shown that the forms of the relationship between D and ε are different, but they all decrease first and then increase with the increase in D . However, inconsistencies in the rate of decrease in ε with D are evident, with a higher rate of decrease observed in certain instances, as indicated by the red dashed line frame in the figure. This can be explained by the fact that at lower D values, ε is triggered by surface wind stress and surface buoyancy flux, and this effect diminishes as D increases. Similarly, as shown in the blue dashed line frame, ε increases as D increases near the bottom boundary, which indicates the influence of the seafloor on turbulent mixing. Elevated ε values are observed near the upper and bottom boundaries. Previous studies [46,47] have suggested that $K\rho$ diminishes rapidly from the seafloor and slowly decays within the water column. In other words, the influence of the bottom boundary layer decreases as the distance from the seafloor increases. We also observed this phenomenon; furthermore, we found similar events in the upper boundary, providing important insights for the parameterization of ε .

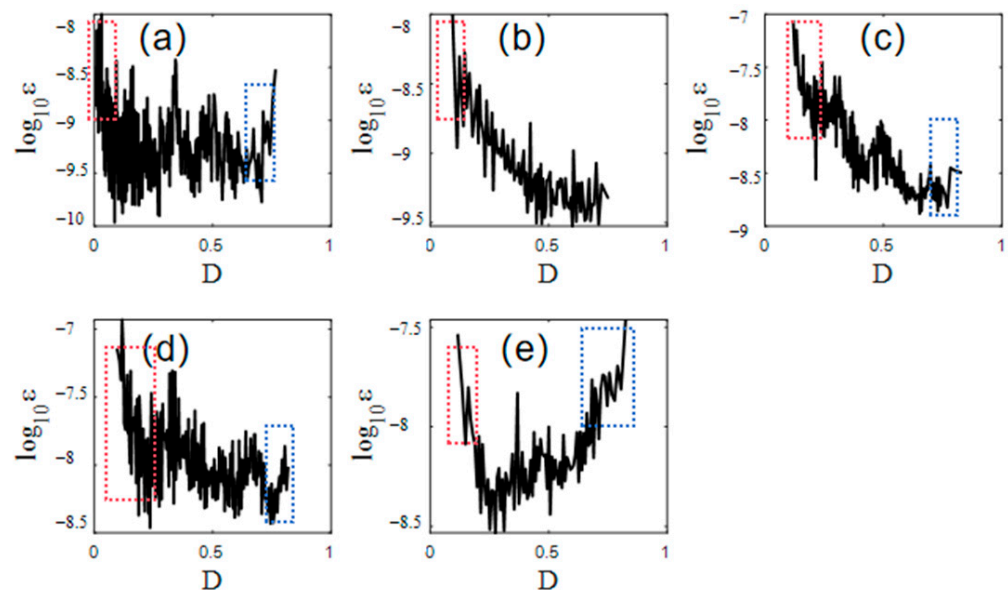


Figure 6. The relationship between D and ε . (a) Results in April–May 2010, (b) results in February 2012, (c) results in July 2012, (d) results in July 2016, and (e) results in July 2018. The dashed frames represent the influence of surface wind stress and buoyancy flux (red dashed frame) and seafloor turbulent mixing (blue dashed frame).

4.2. Depth-Dependent IMG Model

The role of D has been clarified, and the next step is to establish a revised parameterization framework. Introducing D directly influences the vertical distribution of the dissipation rate, where typical vertical structure functions are often exponential or simpler [3,14,54–56]. To ensure that D effectively controls the decay rate of dissipation, we parameterize it in the form of $10^{\alpha+\beta D}$, where α and β are undetermined constants. Notably, β is negative in the upper mixing layer and positive at the bottom, with regional variations expected.

The decay pattern has been confirmed in form, implying that the trend of dissipation rate variation can be well estimated. However, M is the key determinant of the magnitude of turbulent energy dissipation rates. Why do dissipation rates differ significantly at different times and locations? Through analysis of field observations from five cruise observations, we found that ε in the continental shelf sea east of Hainan Island was lowest in July 2012. This is attributed to the presence of coastal upwelling in this area, which strengthens stratification and thus inhibits mixing [34]. The correlation between the average dissipation rate and average stratification for the five cruise observations reached -0.38 , indicating that N is the key parameter determining the dissipation rate. Therefore, we attempt to introduce N into M to determine the order of magnitude of the dissipation rate. N acts as a suppression factor for dissipation rates, and the common and simple method of introduction is subtraction and division. The observed maximum and minimum dissipation rates differ by five orders of magnitude, and division rather than subtraction better captures this variation. Therefore, the form of M can be assumed to be:

$$M = \frac{10^{\alpha+\beta D}}{N^\gamma} \quad (4)$$

where α , β , and γ are undetermined constants, which may be a constant related to location. Therefore, the MG scheme has been rewritten into the following improved MG model (IMG model):

$$\varepsilon = \begin{cases} \frac{10^{\alpha_1+\beta_1 D}}{N^{\gamma_1}} \times S, \text{upper mixed layer} \\ \frac{10^{\alpha_2+\beta_2 D}}{N^{\gamma_2}} \times S, \text{stratified layer} \\ \frac{10^{\alpha_3+\beta_3 D}}{N^{\gamma_3}} \times S, \text{bottom mixed layer} \end{cases} \quad (5)$$

The basic form of the IMG model is given, and an attempt is made to obtain a parameterization scheme suitable for the NSCS for a long time. We use least squares to fit specific values for α , β , and γ .

We use a cross-validation approach to verify the suitability of the IMG model. Four sets of observational data are used for fitting at a time, and the remaining observational data sets are used to verify the fitting effect. The r value of the cross-validation results is greater than 0.65, and the RMSE is less than 0.32. The upper mixed layer values for α , β , and γ are -5.5 , -1.5 , and 0.2 , respectively. The values for the stratified layers are -7.5 , -1 , and 1.1 , respectively. The values for the bottom mixed layer are -9 , 1 , and 0.5 , respectively. This is a remarkable result, showing that ε always maintains the same relationship with N , S , and D . Thus, we obtain the IMG model:

$$\varepsilon = \begin{cases} \frac{10^{-5.5-1.5 \times D}}{N^{0.2}} \times S, \text{upper mixed layer} \\ \frac{10^{-7.5-D}}{N^{1.1}} \times S, \text{stratified layer} \\ \frac{10^{-9+D}}{N^{0.5}} \times S, \text{bottom mixed layer} \end{cases} \quad (6)$$

4.3. Validation of the IMG Model

4.3.1. Applicability of IMG Model in the NSCS

Figure 7 shows the performance of the IMG model for five cruise observations, with results from April–May 2010 (Figure 7a), February and July 2010 (Figure 7b,c), July 2016 (Figure 7d), and July 2018 (Figure 7e). The IMG can better estimate ε , and the estimation error of the upper and lower mixed layers is reduced. Table 3 compares the IMG and MG models, demonstrating that the IMG model can better estimate ε . The IMG model simulations show a high r with the observed $\log_{10}\varepsilon$, with r values of 0.80, 0.65, 0.75, 0.84, and 0.89, and RMSE of 0.23, 0.36, 0.25, 0.19, and 0.22, respectively. These results indicate

an improvement in r by at least 19% and a reduction in RMSE by at least 12%. In the estimation in July 2012, the IMG model showed a 53% higher r than the MG model, with a 44% lower RMSE. This indicates that the IMG is least affected by upwelling. The mean r between the estimated and observed $\log_{10}\epsilon$ of the IMG model is 0.79, which is 49% higher than the MG model, and the mean RMSE is 0.25, which is 42% lower than the MG model.

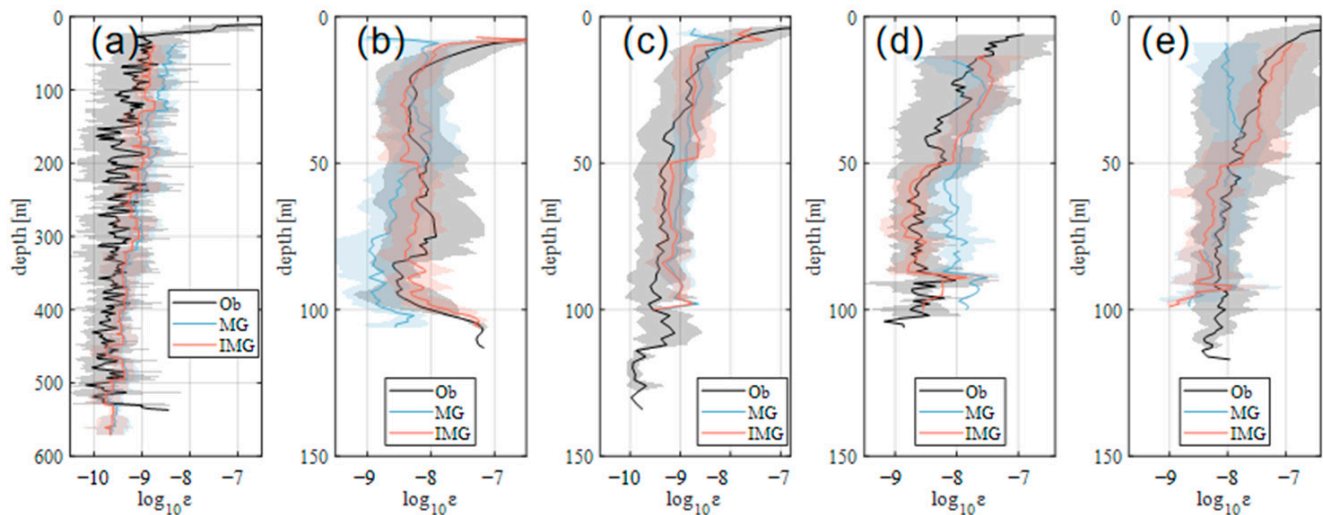


Figure 7. Comparison of depth-averaged profiles of observed and estimated $\log_{10}\epsilon$ in five cruise observations. (a) Results in April–May 2010, (b) results in February 2012, (c) results in July 2012, (d) results in July 2016, and (e) results in July 2018.

Table 3. The r and RMSE between the $\log_{10}\epsilon$ estimated by IMG and the $\log_{10}\epsilon$ observed for five cruise observations.

Model	April–May (2010)		February (2012)		July (2012)		July (2016)		July (2018)	
	r	RMSE	r	RMSE	r	RMSE	r	RMSE	r	RMSE
IMG	0.80	0.23	0.65	0.36	0.75	0.25	0.84	0.19	0.89	0.22
MG	0.63	0.49	0.46	0.43	0.49	0.45	0.68	0.51	0.39	0.25

4.3.2. Detailed Estimates

To understand the IMG model's estimation capabilities in more detail, Figure 8 shows the estimates for each observation station in April–May 2010. Figure 8a,d, Figure 8b,e, and Figure 8c,f show the average $\log_{10}\epsilon$ of 0–50 m, 51–200 m, and deeper than 200 m, respectively. Estimates for other cruises are shown in Figures S5–S8. In a few stations, there may be errors between observed and estimated $\log_{10}\epsilon$ due to different data collection regions. Overall, the estimated dissipation rate exhibits patterns similar to observations in both horizontal and vertical spaces, with errors mostly not exceeding one order of magnitude. The IMG model has relatively large estimation errors for extremely high or low dissipation rates. When there are extreme values of N or S , the error is also significant (Figures S5–S8). In Figure S8, the estimation of the dissipation rate in the Qiongzhou Strait is poor because most of the data used in data fitting are observation stations in the continental shelf sea east of Hainan Island. However, considering that this is a long-term, large-scale parameterization scheme that can be estimated in the upwelling area of eastern Hainan Island in summer, as well as the influence of topography and internal waves in the NSCS, these errors are within an acceptable range.

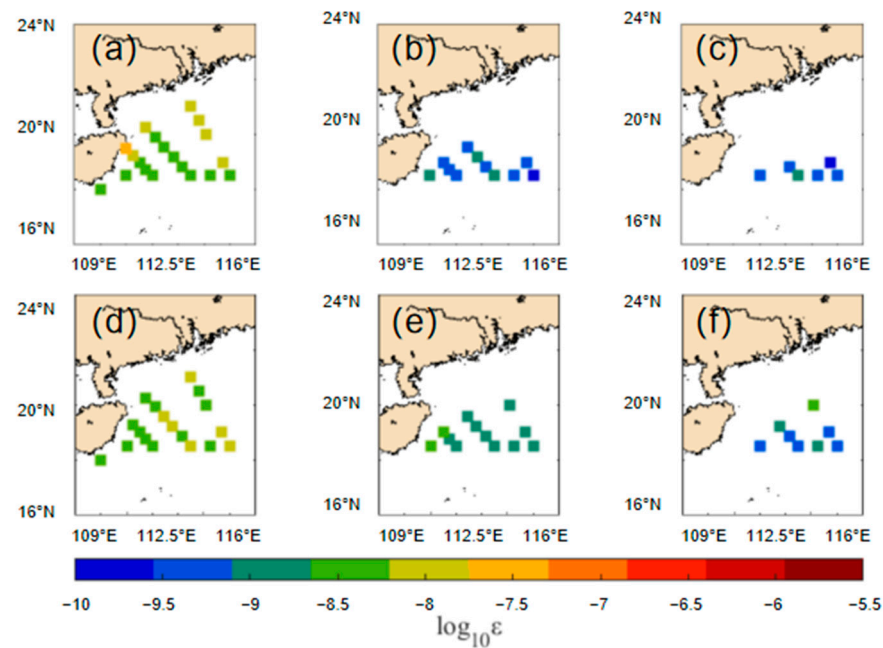


Figure 8. The dissipation rate estimated by the IMG model and the observed dissipation rate in April–May 2010: (a–c) observations and (d–f) estimations.

Theoretical aspects of the MG model assume that ε_0 is a constant based on ocean background values, while in our study, we find that the value of ε_0 depends significantly on observational data. The observed dissipation rate largely depends on the stratification; therefore, in this study, ε_0 is considered a function related to stratification. The proposal of the MG model is based on stratified regions, but in our observations in Section 4.1, we noticed a decrease in mixing intensity from top to bottom in the upper mixed layer. ε undergoes significant variations with N in both time and horizontal space, as well as with D in vertical space. Mackinnon and Gregg treated the typical test wave energy density, vertical wave number, and horizontal wave number as unknown constants [15]. However, we apply the MG model to the full water depth, which means the MG model is not entirely correct in the three proposed assumptions. The NSCS has a variety of turbulent mixing triggering mechanisms, so we hypothesize that they are related to N and D , which implies that constraints of N and D should be added when parameterizing M . Under such assumptions, we can develop a turbulent mixing parameterization scheme applicable to the entire water depth. In this context, we find that disregarding wave–wave interactions, the updated parameterization formula seems to be more consistent with physical principles—strong stratification can suppress mixing, while shear promotes mixing.

When we parameterize M , we actually use N , S , D to determine the key parameter ε_0 in the MG model, which means that N , S , D can roughly determine the average mixing of the observations. Since microstructure data are obtained from oceanic areas with significant differences in contributions from tides, internal waves, mesoscale, etc., distinguishing different profiles of turbine energy distribution rate solely based on these simple variables is an encoding result. This holds exciting prospects for the parameterization of mixing, which is not overly sensitive to the processes generating turbulence.

5. Discussion

5.1. Stability of Parameterization Schemes During Tropical Cyclones

During five observational periods, internal waves and upwellings demonstrated the IMG model's capability to handle sudden oceanic events. Here, we evaluate the impact of

tropical cyclones (TCs) on the stability and performance of IMG. TCs extract significant heat from the ocean, causing sea surface cooling [57,58], while strong winds inject momentum into the upper ocean, generating intense currents [59–61]. When vertical shearing from these currents exceeds the stabilizing effects of stratification, vigorous vertical mixing occurs [62]. Accurate estimation of turbulent mixing before and after a TC passes is essential for understanding its influence. While previous studies proposed mixing parameterization schemes in the NSCS, their performance under TC conditions remains uncertain. To address this, we analyze microstructure data from the offshore eastern of Hainan Island in July 2013, when severe tropical storm Jebi passed through the study area. Figure 9 shows the observational stations (yellow points) and Jebi's track (black dashed line), with Figure 9a,b representing positions before and after Jebi's passage, respectively.

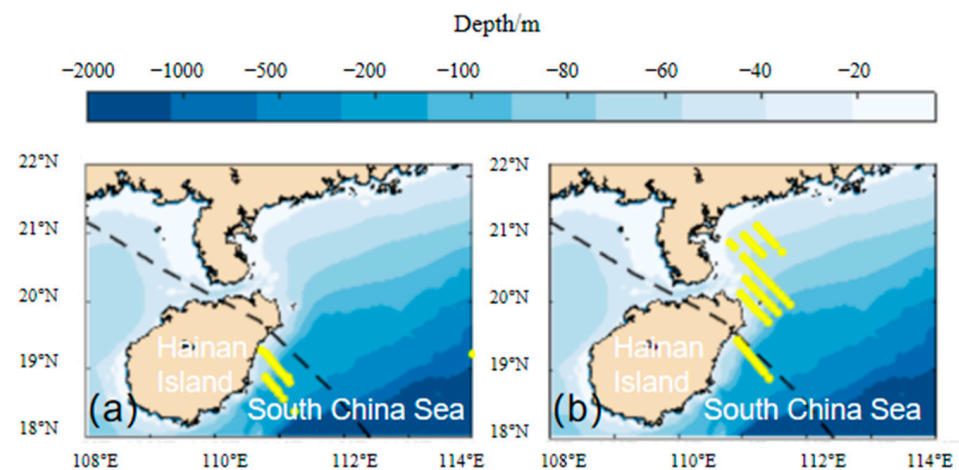


Figure 9. Topographic map of the South China Sea, along with the observed stations collected from 2013. (a) Stations before Jebi's passage. (b) Stations after Jebi's passage.

The performance of the MG and IMG models is compared before and after Jebi's passage (Figure 10a,b). IMG consistently outperformed MG, with r values of 0.83 and 0.29 and RMSE of 0.33 and 0.42. The RMSE estimated by IMG is at least 31% lower than that of MG (Table 4). The successful simulation of ε by IMG is encouraging, providing a reliable tool for studying TC-induced turbulent mixing. This demonstrates that IMG can handle complex situations like tropical cyclone passage with ease, expanding its applicability.

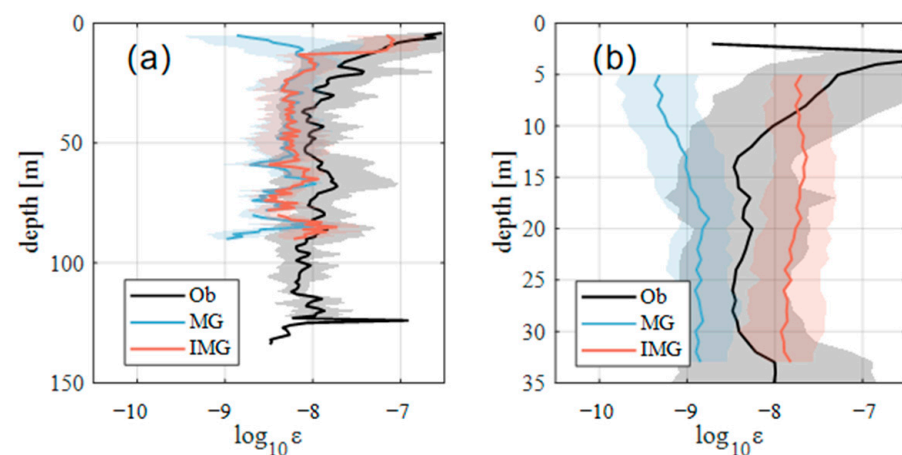


Figure 10. Comparison of depth-averaged profiles of observed and estimated $\log_{10}\varepsilon$: (a) results before Jebi; (b) results after Jebi.

Table 4. The r and RMSE between the $\log_{10}\varepsilon$ estimated by IMG and the $\log_{10}\varepsilon$ observed before and after Jebi.

Model	Before		After	
	r	RMSE	r	RMSE
IMG	0.83	0.33	0.29	0.42
MG	−0.04	0.48	−0.83	0.65

5.2. Prospect of IMG Model

In previous empirical parameterizations, the decay scale hr is defined as a physical length scale in meters. For example, Hasumi and Sugimotohara [52] used 700 m, while St. Laurent et al. [48] adopted 500 m. Decloedt and Luther [46] suggested that in regions with varying roughness in the open ocean (depths: 3000–5000 m), hr ranges from 170 to 670 m. These studies predominantly focused on deep-sea environments at depths of several thousand meters, raising questions about their applicability to shallower regions. Intuitively, decay scales in shallower seas are expected to be shorter. For instance, Lu et al. [5] proposed a decay scale of 44 m at a depth of 200 m and 440 m at 2000 m, consistent with shorter decay scales in shallower waters. Larger decay scales in deep-sea regions align with earlier findings [46,48]. While previous works addressed bottom decay scales based on observational data, we introduced a new approach by using the mixed layer to represent the decay scale. This method divides the water column into three segments, each with a distinct decay rate, aligning more closely with dynamic processes applicable to diverse topographies. Updated parameterization schemes also capture how ε is directly influenced by stratification. In deep-sea regions with weak and relatively uniform stratification, traditional parameterization methods accurately describe ε , often neglecting stratification effects. However, in dynamically complex regions such as the NSCS, turbulent mixing exhibits significant spatiotemporal variability. Stratification plays a vital role in determining the magnitude of turbulent energy dissipation, reflecting seasonal and regional differences.

There are still some issues in this study. For instance, the application of IMG in the Qiongzhou Strait relied on a single set of mixing data, which, when combined with data from the entire NSCS, is clearly insufficiently robust. These issues will be addressed as more observational data become available. Significant challenges remain, such as the interaction between the SCS positive pressure tide and the steep terrain of the Luzon Strait, which generates strong internal tides [11,23] and large-amplitude internal solitary waves [63,64]. Furthermore, the active near-inertial internal waves in the SCS, driven by prevalent monsoons and frequent tropical cyclones, contribute substantial energy to turbulent mixing [65–67]. These mesoscale processes play a critical role in turbulent kinetic energy dissipation, making mixing mechanisms in the SCS highly complex. The diversity of mixing drivers poses challenges for generalized parameterization models, which may not fully capture all scenarios. However, this study highlights the impacts of coastal upwelling, internal waves, and tropical cyclones on the IMG model. Further experimentation is necessary to validate these findings, and future optimization of parameterization schemes based on dynamic physical processes represents a critical direction for the evolution of the IMG model.

6. Conclusions

This study assesses and improves the applicability of the MG model proposed by MacKinnon and Gregg in 2003 in the NSCS using five micro- and fine-scale observational datasets comprising 237 profiles collected between 2010 and 2018. The key findings are as follows:

1. The estimation error of the MG model in the NSCS exceeds one order of magnitude, particularly in the mixed layer. This large error is partly due to the difficulty in determining the key parameter ε_0 . The study reveals that the MG model's performance varies with different mixing mechanisms across cruises.
2. Analysis using three machine learning methods identified normalized depth (D) as one of the most critical parameters influencing mixing in data-driven models.
3. Incorporating D into the MG model resulted in the improved MG (IMG) model. The IMG model achieved a mean r of 0.79 between estimated and observed $\log_{10}\varepsilon$, at least 49% higher than the MG model, and a mean RMSE of 0.25, at least 42% lower than the MG model.

The IMG model reliably estimates turbulent mixing in the NSCS over multiple years, including during typhoon events. Addressing the “black box” issue in machine learning is essential for advancing artificial intelligence in oceanography. Identifying critical parameters through their importance can enhance our understanding of physical processes, making this a valuable direction for future research.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/jmse13010046/s1>, Figure S1: Similar to Figure 3 in the main text, but the figures for the Apr–May 2010; Figure S2: Similar to Figure 3 in the main text, but the figures for the Jul 2012; Figure S3: Similar to Figure 3 in the main text, but the figures for the Jul 2016; Figure S4: Similar to Figure 3 in the main text, but the figures for the Jul 2018; Figure S5: Similar to Figure 8 in the main text, but for the Feb 2012; Figure S6: Similar to Figure 8 in the main text, but for the Jul 2012; Figure S7: Similar to Figure 8 in the main text, but for the Feb 2016; Figure S8: Similar to Figure 8 in the main text, but for the Feb 2018.

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References

1. Sandstrom, H.; Elliott, J.A. Internal tide and solitons on the Scotian Shelf: A nutrient pump at work. *J. Geophys. Res. Ocean.* **1984**, *89*, 6415–6426. [[CrossRef](#)]
2. Kraus, E.B.; Turner, J.S. A one-dimensional model of the seasonal thermocline II. The general theory and its consequences. *Tellus* **1967**, *19*, 98–106.
3. Bryan, K.; Lewis, L.J. A water mass model of the world ocean. *J. Geophys. Res. Ocean.* **1979**, *84*, 2503–2517. [[CrossRef](#)]
4. Qiao, F.; Yuan, Y.; Yang, Y.; Zheng, Q.; Xia, C.; Ma, J. Wave-induced mixed mixing in the upper ocean: Distribution and application to a global ocean circulation model. *Geophys. Res. Lett.* **2004**, *31*, L11306. [[CrossRef](#)]
5. Lu, Y.; Cen, X.; Guo, S.; Qu, L.; Huang, P.; Shang, X.; Zhou, S. Spatial variability of diapycnal mixing in the South China Sea inferred from density overturn analysis. *J. Phys. Oceanogr.* **2021**, *51*, 3417–3434. [[CrossRef](#)]

6. Mellor, G.L.; Yamada, T. Development of a turbulence closure model for geophysical fluid problems. *Rev. Geophys.* **1982**, *20*, 851–875. [\[CrossRef\]](#)
7. Pacanowski, R.C.; Philander, S.G.H. Parameterization of vertical mixing in numerical models of tropical oceans. *J. Phys. Oceanogr.* **1981**, *11*, 1443–1451. [\[CrossRef\]](#)
8. Chen, D.; Rothstein, L.M.; Busalacchi, A.J. A hybrid vertical mixing scheme and its application to tropical ocean models. *J. Phys. Oceanogr.* **1994**, *24*, 2156–2179. [\[CrossRef\]](#)
9. Large, W.G.; McWilliams, J.C.; Doney, S.C. Oceanic vertical mixing: A review and a model with a nonlocal boundary layer parameterization. *Rev. Geophys.* **1994**, *32*, 363–403. [\[CrossRef\]](#)
10. St. Laurent, L. Turbulent dissipation on the margins of the South China Sea. *Geophys. Res. Lett.* **2008**, *35*, 23. [\[CrossRef\]](#)
11. Alford, M.H.; MacKinnon, J.A.; Nash, J.D.; Simmons, H.; Pickering, A.; Klymak, J.M.; Lu, C.W. Energy flux and dissipation in Luzon Strait: Two tales of two ridges. *J. Phys. Oceanogr.* **2011**, *41*, 2211–2222. [\[CrossRef\]](#)
12. Liu, Z.; Lozovsky, I. Upper pycnocline turbulence in the northern South China Sea. *Chin. Sci. Bull.* **2012**, *57*, 2302–2306. [\[CrossRef\]](#)
13. Gregg, M.C. Scaling turbulent dissipation in the thermocline. *J. Geophys. Res. Ocean.* **1989**, *94*, 9686–9698. [\[CrossRef\]](#)
14. Kunze, E.; Firing, E.; Hummon, J.M.; Chereskin, T.K.; Thurnherr, A.M. Global abyssal mixing inferred from lowered ADCP shear and CTD strain profiles. *J. Phys. Oceanogr.* **2006**, *36*, 1553–1576. [\[CrossRef\]](#)
15. MacKinnon, J.A.; Gregg, M.C. Shear and baroclinic energy flux on the summer New England shelf. *J. Phys. Oceanogr.* **2003**, *33*, 1462–1475. [\[CrossRef\]](#)
16. Thorpe, S.A. Turbulence and mixing in a Scottish loch. *Philos. Trans. R. Soc. Lond. Ser. A* **1977**, *286*, 125–181.
17. Dillon, T.M. Vertical overturns: A comparison of Thorpe and Ozmidov length scales. *J. Geophys. Res. Ocean.* **1982**, *87*, 9601–9613. [\[CrossRef\]](#)
18. Gutjahr, O.; Brüggemann, N.; Haak, H.; Jungclaus, J.H.; Putrasahan, D.A.; Lohmann, K.; von Storch, J.S. Comparison of ocean vertical mixing schemes in the Max Planck Institute Earth System Model (MPI-ESM1.2). *Geosci. Model Dev.* **2021**, *14*, 2317–2349. [\[CrossRef\]](#)
19. Jia, Y.; Richards, K.J.; Annamalai, H. The impact of vertical resolution in reducing biases in sea surface temperature in a tropical Pacific Ocean model. *Ocean Model.* **2021**, *157*, 101722. [\[CrossRef\]](#)
20. Zhu, Y.; Zhang, R.; Moum, J.N.; Wang, F.; Li, X.; Li, D. Physics-informed deep-learning parameterization of ocean vertical mixing improves climate simulations. *Nat. Sci. Rev.* **2022**, *9*, nwac044. [\[CrossRef\]](#)
21. Mashayek, A.; Reynard, N.; Zhai, F.; Srinivasan, K.; Jelley, A.; Naveira Garabato, A.; Caulfield, C.C.P. Deep ocean learning of small-scale turbulence. *Geophys. Res. Lett.* **2022**, *49*, e2022GL098039. [\[CrossRef\]](#)
22. Hu, M.; Xie, L.; Li, M.; Zheng, Q. Parameterization of turbulent mixing by deep learning in the continental shelf sea east of Hainan Island. *J. Oceanol. Limnol.* **2024**. Available online: <https://jol.iocasjournals.cn/thesisDetails?columnId=75673717&Fpath=home&index=0&lang=en> (accessed on 27 December 2024).
23. Alford, M.H.; Peacock, T.; MacKinnon, J.A.; Nash, J.D.; Buijsman, M.C.; Centurioni, L.R.; Tang, T.Y. The formation and fate of internal waves in the South China Sea. *Nature* **2015**, *521*, 65–69. [\[CrossRef\]](#) [\[PubMed\]](#)
24. Tian, J.; Yang, Q.; Zhao, W. Enhanced diapycnal mixing in the South China Sea. *J. Phys. Oceanogr.* **2009**, *39*, 3191–3203. [\[CrossRef\]](#)
25. Klymak, J.M.; Alford, M.H.; Pinkel, R.; Lien, R.C.; Yang, Y.J.; Tang, T.Y. The breaking and scattering of the internal tide on a continental slope. *J. Phys. Oceanogr.* **2011**, *41*, 926–945. [\[CrossRef\]](#)
26. Buijsman, M.C.; Legg, S.; Klymak, J. Double-ridge internal tide interference and its effect on dissipation in Luzon Strait. *J. Phys. Oceanogr.* **2012**, *42*, 1337–1356. [\[CrossRef\]](#)
27. Gregg, M.C.; Sanford, T.B.; Winkel, D.P. Reduced mixing from the breaking of internal waves in equatorial waters. *Nature* **2003**, *422*, 513–515. [\[CrossRef\]](#)
28. Yang, Q.; Zhao, W.; Liang, X.; Tian, J. Three-dimensional distribution of turbulent mixing in the South China Sea. *J. Phys. Oceanogr.* **2016**, *46*, 769–788. [\[CrossRef\]](#)
29. Sun, H.; Yang, Q.; Zhao, W.; Liang, X.; Tian, J. Temporal variability of diapycnal mixing in the northern South China Sea. *J. Geophys. Res. Ocean.* **2016**, *121*, 8840–8848. [\[CrossRef\]](#)
30. Lu, Z.; Chen, G.; Xie, X.; Xu, X.; Shang, X. Research on microstructural characteristics of marine mixing in the northern South China Sea. *Prog. Nat. Sci.* **2009**, *19*, 657–663.
31. Shang, X.; Liang, C.; Chen, G. Spatial distribution of turbulent mixing in the upper ocean of the South China Sea. *Ocean Sci.* **2017**, *13*, 503–519. [\[CrossRef\]](#)
32. Liang, C.; Chen, G.; Shang, X. Observations of the turbulent kinetic energy dissipation rate in the upper central South China Sea. *Ocean Dyn.* **2017**, *67*, 597–609. [\[CrossRef\]](#)
33. Sun, H.; Yang, Q.; Tian, J. Microstructure measurements and finescale parameterization assessment of turbulent mixing in the northern South China Sea. *J. Oceanogr.* **2018**, *74*, 485–498. [\[CrossRef\]](#)

34. Li, M.; Xie, L.; Zong, X.; Zhang, S.; Zhou, L.; Li, J. The cruise observation of turbulent mixing in the upwelling region east of Hainan Island in the summer of 2012. *Acta Oceanol. Sin.* **2018**, *37*, 1–12. [\[CrossRef\]](#)
35. MacKinnon, J.A.; Gregg, M.C. Spring mixing: Turbulence and internal waves during restratification on the New England shelf. *J. Phys. Oceanogr.* **2005**, *35*, 2425–2443. [\[CrossRef\]](#)
36. Palmer, M.R.; Rippeth, T.P.; Simpson, J.H. An investigation of internal mixing in a seasonally stratified shelf sea. *J. Geophys. Res. Ocean.* **2008**, *113*, C12. [\[CrossRef\]](#)
37. Van der Lee, E.M.; Umlauf, L. Internal wave mixing in the Baltic Sea: Near-inertial waves in the absence of tides. *J. Geophys. Res. Ocean.* **2011**, *116*, C10. [\[CrossRef\]](#)
38. Xie, X.; Cuyppers, Y.; Bouruet-Aubertot, P.; Ferron, B.; Pichon, A.; Lourenço, A.; Cortes, N. Large-amplitude internal tides, solitary waves, and turbulence in the central Bay of Biscay. *Geophys. Res. Lett.* **2013**, *40*, 2748–2754. [\[CrossRef\]](#)
39. Dong, C.; Xu, G.; Han, G.; Bethel, B.J.; Xie, W.; Zhou, S. Recent developments in artificial intelligence in oceanography. *Ocean Land Atmos. Res.* **2022**, *2022*, 9870950. [\[CrossRef\]](#)
40. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
41. Altmann, A.; Toloşi, L.; Sander, O.; Lengauer, T. Permutation importance: A corrected feature importance measure. *Bioinformatics* **2010**, *26*, 1340–1347. [\[CrossRef\]](#)
42. Lundberg, S.M.; Erion, G.; Chen, H.; DeGrave, A.; Prutkin, J.M.; Nair, B.; Lee, S.I. From local explanations to global understanding with explainable AI for trees. *Nat. Mach. Intell.* **2020**, *2*, 56–67. [\[CrossRef\]](#) [\[PubMed\]](#)
43. Polzin, K.L.; Toole, J.M.; Ledwell, J.R.; Schmitt, R.W. Spatial variability of turbulent mixing in the abyssal ocean. *Science* **1997**, *276*, 93–96. [\[CrossRef\]](#) [\[PubMed\]](#)
44. Wu, L.; Jing, Z.; Riser, S.; Visbeck, M. Seasonal and spatial variations of Southern Ocean diapycnal mixing from Argo profiling floats. *Nat. Geosci.* **2011**, *4*, 363–366. [\[CrossRef\]](#)
45. Wunsch, C.; Ferrari, R. Vertical mixing, energy, and the general circulation of the oceans. *Annu. Rev. Fluid Mech.* **2004**, *36*, 281–314. [\[CrossRef\]](#)
46. Decloedt, T.; Luther, D.S. On a simple empirical parameterization of topography-catalyzed diapycnal mixing in the abyssal ocean. *J. Phys. Oceanogr.* **2010**, *40*, 487–508. [\[CrossRef\]](#)
47. Waterhouse, A.F.; MacKinnon, J.A.; Nash, J.D.; Alford, M.H.; Kunze, E.; Simmons, H.L.; Lee, C.M. Global patterns of diapycnal mixing from measurements of the turbulent dissipation rate. *J. Phys. Oceanogr.* **2014**, *44*, 1854–1872. [\[CrossRef\]](#)
48. St. Laurent, L.C.; Simmons, H.L.; Jayne, S.R. Estimating tidally driven mixing in the deep ocean. *Geophys. Res. Lett.* **2002**, *29*, 211–214. [\[CrossRef\]](#)
49. Moum, J.N. Energy-containing scales of turbulence in the ocean thermocline. *J. Geophys. Res. Ocean.* **1996**, *101*, 14095–14109. [\[CrossRef\]](#)
50. Nash, J.D.; Kunze, E.; Toole, J.M.; Schmitt, R.W. Internal tide reflection and turbulent mixing on the continental slope. *J. Phys. Oceanogr.* **2004**, *34*, 1117–1134. [\[CrossRef\]](#)
51. Gargett, A.E. Vertical eddy diffusivity in the ocean interior. *J. Mar. Res.* **1984**, *42*, 359–393. [\[CrossRef\]](#)
52. Hasumi, H.; Sugimoto, N. Effects of locally enhanced vertical diffusivity over rough bathymetry on the world ocean circulation. *J. Geophys. Res. Ocean.* **1999**, *104*, 23367–23374. [\[CrossRef\]](#)
53. Klymak, J.M.; Pinkel, R.; Liu, C.T.; Liu, A.K.; David, L. Prototypical solitons in the South China Sea. *Geophys. Res. Lett.* **2006**, *33*, 11. [\[CrossRef\]](#)
54. Armi, L. Some evidence for boundary mixing in the deep ocean. *J. Geophys. Res. Ocean.* **1978**, *83*, 1971–1979. [\[CrossRef\]](#)
55. Garrett, C.; Gilbert, D. Estimates of vertical mixing by internal waves reflected off a sloping bottom. *Elsevier Oceanogr. Ser.* **1988**, *46*, 405–423.
56. Toole, J.M.; Schmitt, R.W.; Polzin, K.L.; Kunze, E. Near-boundary mixing above the flanks of a midlatitude seamount. *J. Geophys. Res. Ocean.* **1997**, *102*, 947–959. [\[CrossRef\]](#)
57. Cione, J.J.; Uhlhorn, E.W. Sea surface temperature variability in hurricanes: Implications with respect to intensity change. *Mon. Weather Rev.* **2003**, *131*, 1783–1796. [\[CrossRef\]](#)
58. Emanuel, K.; DesAutels, C.; Holloway, C.; Korty, R. Environmental control of tropical cyclone intensity. *J. Atmos. Sci.* **2004**, *61*, 843–858. [\[CrossRef\]](#)
59. Fan, Y.; Ginis, I.; Hara, T.; Wright, C.W.; Walsh, E.J. Numerical simulations and observations of surface wave fields under an extreme tropical cyclone. *J. Phys. Oceanogr.* **2009**, *39*, 2097–2116. [\[CrossRef\]](#)
60. Jarosz, E.; Mitchell, D.A.; Wang, D.W.; Teague, W.J. Bottom-up determination of air-sea momentum exchange under a major tropical cyclone. *Science* **2007**, *315*, 1707–1709. [\[CrossRef\]](#)
61. Sun, R.; Villas Bôas, A.B.; Subramanian, A.C.; Cornuelle, B.D.; Mazloff, M.R.; Miller, A.J.; Langodan, S.; Hoteit, I. Focusing and defocusing of tropical cyclone generated waves by ocean current refraction. *J. Geophys. Res. Ocean.* **2022**, *127*, e2021JC018112. [\[CrossRef\]](#)
62. Zhang, H.; He, H.; Zhang, W.Z.; Tian, D. Upper ocean response to tropical cyclones: A review. *Geosci. Lett.* **2021**, *8*, 1. [\[CrossRef\]](#)

63. Wang, H.; Jia, Y.; Ji, C.; Jiang, W.; Bian, C. Internal tide-induced turbulent mixing and suspended sediment transport at the bottom boundary layer of the South China Sea slope. *J. Mar. Syst.* **2022**, *230*, 103723. [[CrossRef](#)]
64. Lien, R.C.; Tang, T.Y.; Chang, M.H.; d'Asaro, E.A. Energy of nonlinear internal waves in the South China Sea. *Geophys. Res. Lett.* **2005**, *32*, 5. [[CrossRef](#)]
65. Cao, A.; Guo, Z.; Song, J.; Lv, X.; He, H.; Fan, W. Near-inertial waves and their underlying mechanisms based on the South China Sea internal wave experiment (2010–2011). *J. Geophys. Res. Ocean.* **2018**, *123*, 5026–5040. [[CrossRef](#)]
66. Chen, G.; Xue, H.; Wang, D.; Xie, Q. Observed near-inertial kinetic energy in the northwestern South China Sea. *J. Geophys. Res. Ocean.* **2013**, *118*, 4965–4977. [[CrossRef](#)]
67. Shang, C.; Liang, C.; Chen, G.; Gao, Y. The influence of turbulent mixing on the subsurface chlorophyll maximum layer in the northern South China Sea. *J. Oceanol. Limnol.* **2021**, *39*, 2167–2180. [[CrossRef](#)]

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