This paper introduces an observational dataset of submesoscale eddies in the Northwest Pacific using deep learning techniques. While the approach and resulting product are novel, certain crucial results and discussions are missing. Specifically, this article exhibits significant language issues, including numerous grammar errors and unclear expression. I might consider accepting this article after these issues are truly resolved.

(1) Even though a precise definition of 'submesoscale eddy' is not yet established, the authors should provide a descriptive introduction to the fundamental characteristics (shape, size, structure, etc.). This is crucial for readers to comprehend the dataset. The authors' efforts in reviewing previous research are incomplete, as there is no mention of Munk's groundbreaking work in 2002.

Response: Thanks for your comments. I read "Spirals on the Sea", and its three questions tried to answer initially explained some of the fundamental characteristics of spirals. The first paragraph of the introduction describes the spatio-temporal characteristics, structure, formation and role of submesoscale eddies (SMEs). I added the following sentence in line 25 "SMEs' spirals on the sea are considered a result of the cat's eye circulation associated with horizontal shear instability (Munk et al., 2000)". Currently, the introduction is enough as describing the detection of SMEs, despite many attempts in various articles to elucidate additional characteristics, such as the reason for the superior quality of cyclonic spirals over anticyclonic spirals, and this involves a lot of theories about the physical oceans.

(2) Compared to logarithmic transformation, the CLAHE image enhancement technique can provide clearer information about spiral structures, but whether the enhanced signals are genuine and whether they might exaggerate the size and intensity of submesoscale eddies, these aspects need to be elucidated through some results.

Response: Thanks for your comments. Another example is that CLAHE technology is also applied to medical images to identify lesions more clearly(Sonali et al., 2019). From a mathematical point of view, the CLAHE technique only performs the operation of increasing or decreasing the pixel value and does not create a spiral structure, let alone change the size of the original spiral or the density of the spiral. Additionally, the spirals have only become clearer, rendering them easier to identify by both manual observation and machine recognition from the zoomed-in Fig. 3 (a) and (c). And the main purpose of this dataset is to find out their location regardless of intensity.

(3) L125. Prior to conducting large-scale identification, the utilization of manual annotation methods is required, undoubtedly introducing significant uncertainty. The authors need to demonstrate that the results of manual annotation are statistically reasonable. Figure 5 presents an eddy with a clear structure. The question arises regarding how eddies with less distinct structures are handled. This also touches on the issue of the definition of submesoscale eddies.

Response: Thanks for your comments. Annotation work has been a major source of uncertainty affecting machine learning outcomes. In the AI identification of mesoscale eddies, people can use the results of the altimeter as the “real eddies” for labelling and model training. Further, the identification of mesoscale eddies by altimeter also requires a tolerance range to define the closed contours and a threshold to determine the size of the eddies. However, there are no conventional algorithms that can adjust physically meaningful parameters to provide “true” SMEs. Therefore, we usually analyze the results to see if our annotation set is missing some other kind of spiral structure such as not isolated, irregular, or more ambiguous. It is worth mentioning that the labelling work lasted for three months and was carried out by two independent people to prevent the wrong labelling of the direction of eddies or the eddies whose spiral structure was not clear. Finally, mAP@0.5 reached 97.32%. Additionally, if you still doubt our annotation set, I can upload it to Zenodo for people to view or would you like to provide what specific statistical analysis was done on the annotation set?

(4) There have been some studies utilizing machine learning methods to detect mesoscale eddies in the ocean. The authors should introduce the related works and highlight the distinction between the submesoscale eddies identified here and mesoscale eddies. Is the difference merely in terms of size?

Response: Thanks for your comments. I made a few additions to the introduction in lines 59-64 “Many studies have utilized machine learning methods to detect, track, and predict mesoscale eddies, owing to the abundance of reliable altimeter observations and the well-developed theory surrounding them(Duo et al., 2019; Choi and Kim, 2018; Franz et al., 2018; Ge et al., 2023; Huang et al., 2022). However, theoretical studies of SMEs lack sufficient observational information because the spatial and temporal resolution of the altimeter is not sufficient for observing them. Despite the availability of other high-resolution observational methods, submesoscale processes are obscured by a variety of large-scale ocean information”. I want to emphasize that the significance of this paper is to provide a large number of eddies that cannot be observed by the altimeter for further SMEs research.

(5) L210. 'at a confidence threshold of 0.2'. This is an exceptionally vital parameter, capable of greatly influencing the eventual product. The authors need to provide a clearer reason for the adoption of this value by means of sensitivity testing. This step is indispensable to eliminate artificial selection and ensure robustness.

Response: Thanks for your comments. I have used this dataset to do some chlorophyll-related analysis and got some results similar to the simulations. I think the eddies above 0.2 confidence are sufficient for statistical analysis. There are some non-artificial interference methods to determine the value of confidence, such as adding confidence as a parameter to the loss function for model training to obtain higher mAP, but in industry applications, the actual effect of identification is more reliable than these parameters. The confidence of 0.2 was chosen because many eddies below 0.2 were wrong so I chose to keep eddies above the confidence of 0.2. It is preferable to cut some SMEs, but also to improve the reliability of the analytical results generated by the dataset.

Additionally, I can upload the full eddies data of the confidence from 0-1. Below Figure I are a few low confidence images.

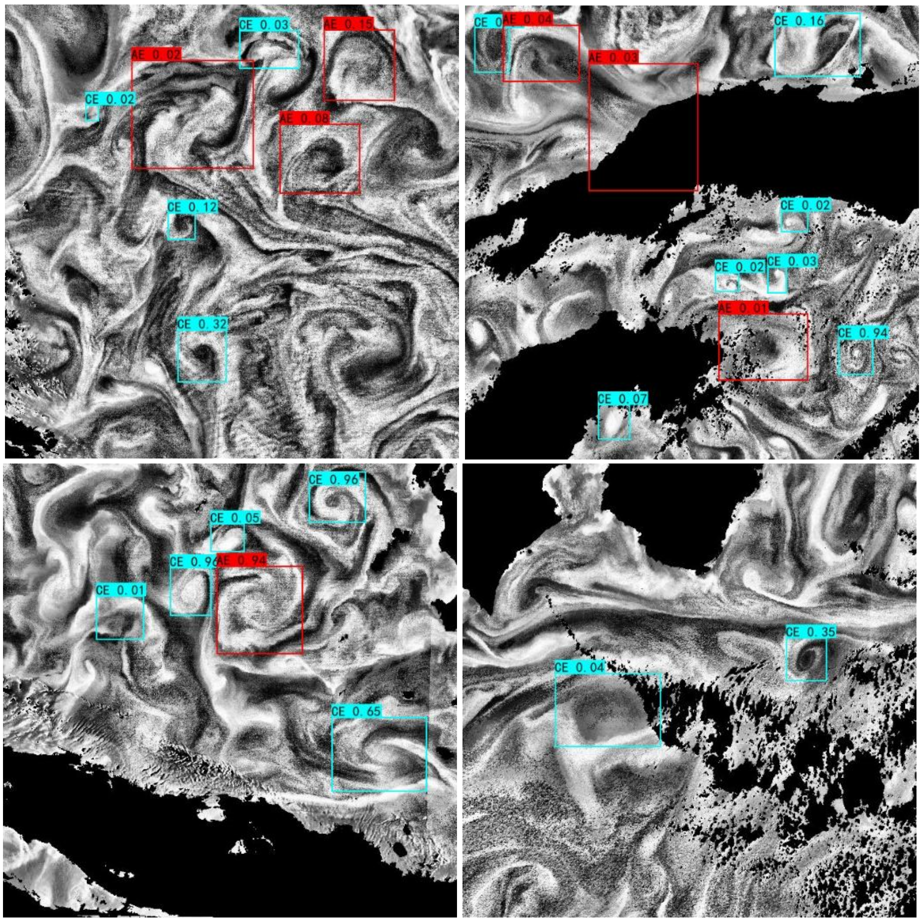

Figure I: Image identification results of SMEs.

We also verify some of the results with different confidence thresholds. As shown in Figure II below, different confidence levels do not affect the conclusions.

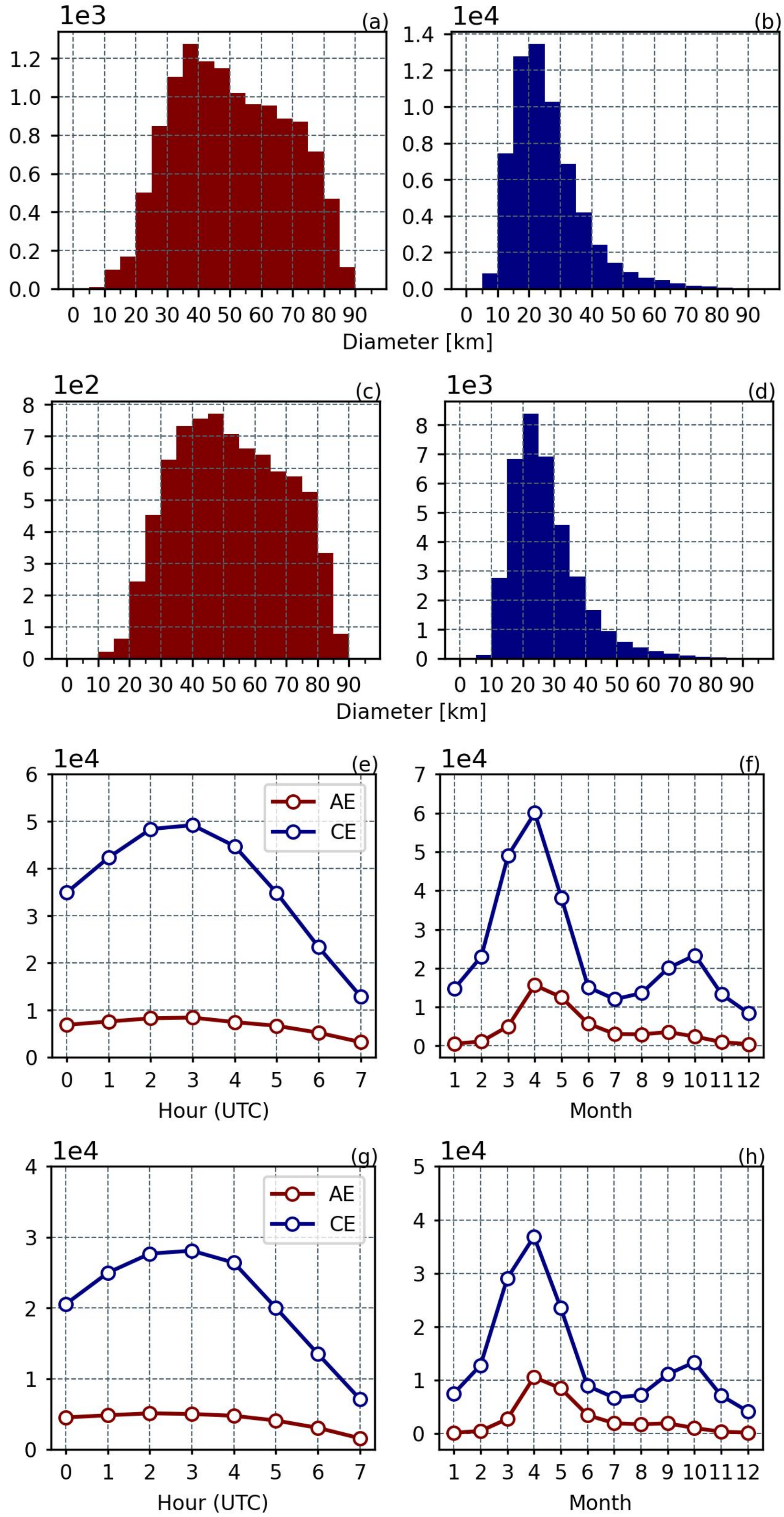

Figure II: (a)(c) and (b)(d) show the diameter distribution histograms of AE and CE, respectively. (e) and (g): The figure shows the variation in the number of identified eddies over hours. (f) and (h): The figure shows the seasonal variation in the number of identified eddies. (a)(b)(e)(f) is the results with a confidence minimum of 0.5 and the confidence minimum of (c)(d)(g)(h) is 0.8.

(6) L230. '…, with the Kuroshio current passing through this area'. Do you mean that the Kuroshio passes through the Sea of Japan?

Response: Thanks for your comments. I'm sorry for the misunderstanding, but I meant that part of the Kuroshio flow into the Sea of Japan. I made changes in line 409 "It is evident that AEs are mainly distributed in the Sea of Japan along the convergence zone of warm and cold currents."

(7) L245. Beyond location and size, is it possible to analyze the lifecycle of submesoscale eddies?

Response: Thanks for your comments. It is entirely possible to track SMEs, but it is certainly more difficult than tracking mesoscale eddies, because the morphology and position of SMEs change faster over time, and a large number of observations are obscured by clouds. I think it's a challenging job.

(8) Sections 3.5 and 3.6 do not show the validation of the detected eddies. These submesoscale eddies are derived from processed chlorophyll images. Can the authors utilize additional observational data to confirm the authenticity of these eddies, for example, high-resolution SST data or other flow observations?

Response: Thanks for your comments. The data observed by remote sensing satellites are often used to prove the authenticity of simulation data, which is a kind of measured data. Additionally, the spatio-temporal resolution of the ocean current data generated by non-simulation is not sufficient to verify the SMEs of observation.

To evade potential contingency arising from single-sensor data, the observation of consistent Chlorophyll (CHL) distributions across different sensors is depicted in Section 3.5. Furthermore, Chapter 3.6 reveals the correlation between the altimeter and the chlorophyll field in terms of their shared eddies. Moreover, the high-resolution chlorophyll field can identify more SMEs.

We have searched the flow field data, but the measured ocean current data do not have a similar temporal-spatial resolution and many of them are interpolated data of reanalysis. As shown in figure III below, the coincidence between the two is not high due to the difference in temporal-spatial resolution, which is why the mesoscale eddies data is directly compared in Section 3.6.

("The GlobCurrent data repository now includes the surface geostrophic current, the Ekman current at the surface and at 15 m depth, and the combined geostrophic and Ekman currents. The data are interpolated and collocated to a common grid with a spatial resolution of 25 km and a temporal resolution of 1 day for the geostrophic current and three hours for the Ekman currents and the combined currents."
https://woc.oceandatalab.com/?from=globcurrent&date=1557230400000)

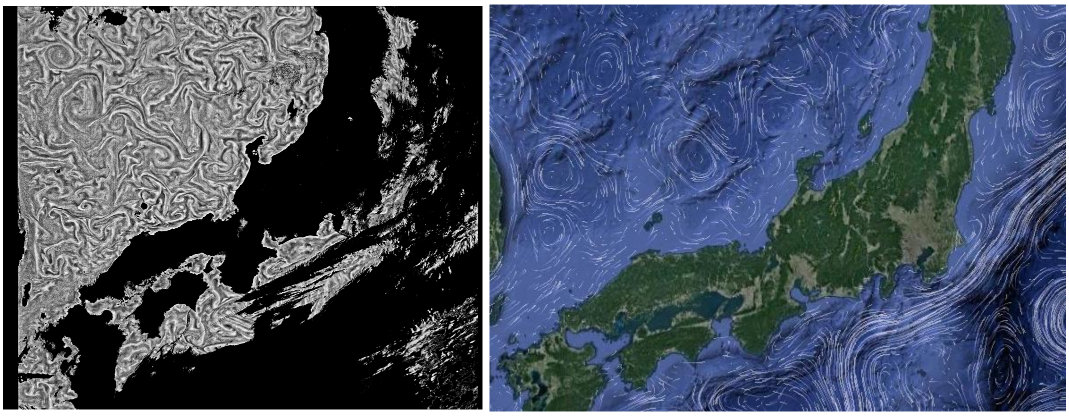

Figure III: A comparison from the Sentinel-3 OLCI enhanced CHL image (left) and ocean current image (right) on May 7, 2019.

Regarding the question of observational validation using high-resolution SST data, we believe that this is more likely to be a new question about the modulation of SST by SMEs. The VIIRS can provide the SST data with a spatial resolution of 750 m at nadir. However, it is not apparent for direct observation.

(9) The color scheme of Figure 12 needs to be changed, as it doesn't clearly present the details.

Response: Thanks for your comments. I changed the color of the cyclone box from blue to white as shown in figure V.

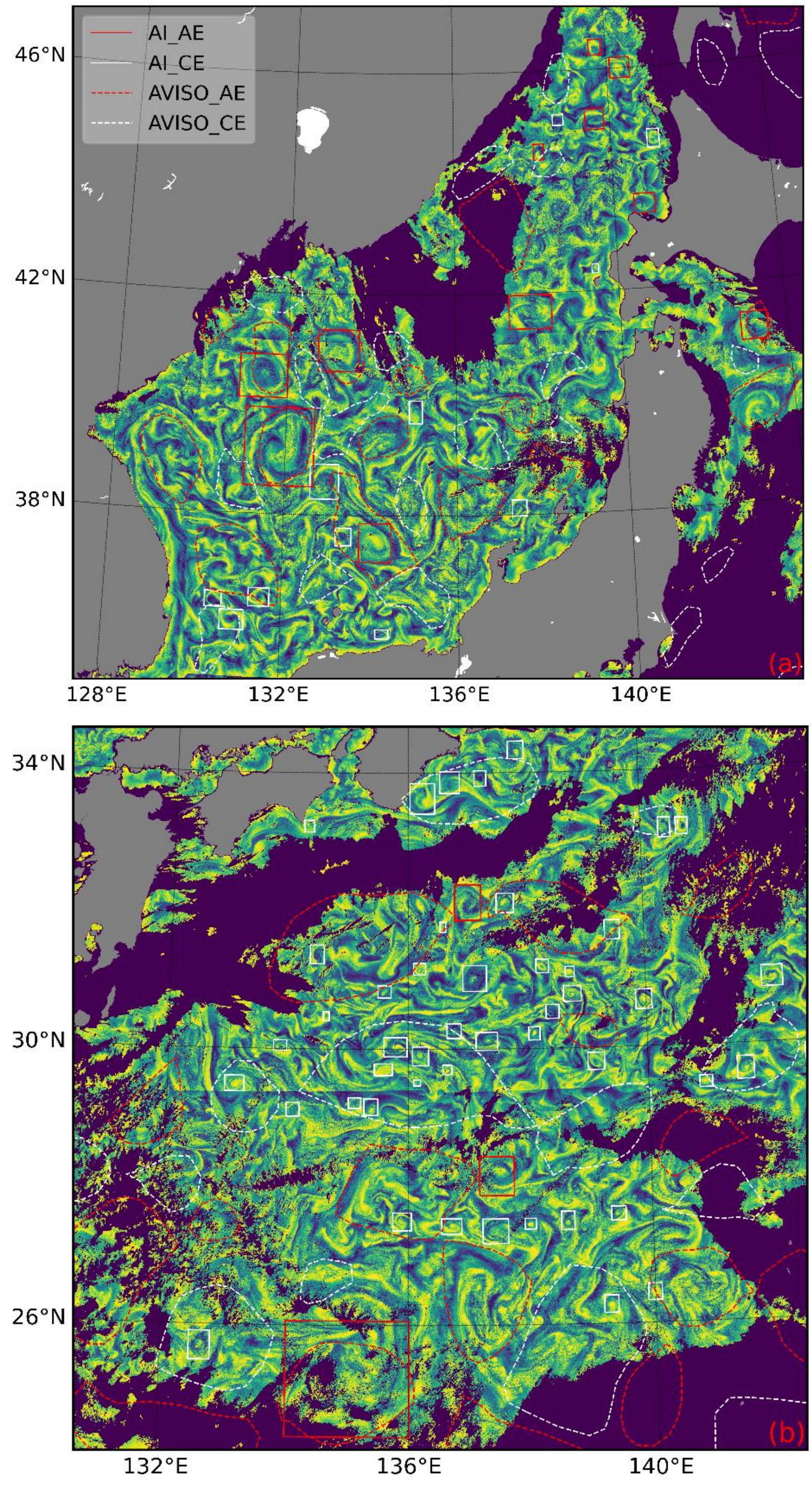

Figure V: A comparison between the AI vortex identification results and the AVISO vortex results on the same day with CHL-enhanced background. (a) and (b) are for May 7, 2019, and April 13, 2011, respectively.

(10) This dataset is regional in nature, focusing on submesoscale eddies in the Northwest Pacific Ocean. This point needs to be clarified in the title of the article, otherwise, readers might assume it's a global eddy dataset.

Response: Thanks for your comments. The "GOCI I" in the title indicates the region and period of the dataset, and Figure 1 shows the coverage area of GOCI I. Our method for identifying SMEs is globally applicable.

(11) For a dataset, especially results derived from observations, there are bound to be certain limitations. The authors need to engage in a discussion in this regard, providing readers with guidance and reminders when utilizing the dataset.

Response: Thanks for your comments. I added some discussion on line 560. "However, there are some limitations in the use of this dataset. First, users should be mindful of the potential for underrepresentation or misidentification of certain features. Second, there is no clear physical definition to determine the boundary of the identified submesoscale eddies. Furthermore, the setting of the confidence threshold may delete a large number of real SMEs, to avoid retaining the identification of disputed eddies. Therefore, careful consideration must be given to the selection of the confidence threshold to satisfy the need of certain research. Nonetheless, the method proposed in this paper successfully detects SMEs, and the presence of chlorophyll spirals induced by SMEs serves as a credible and direct representation of their physical properties within the chlorophyll field. These research results have important scientific significance for a deeper understanding of the role of SMEs in marine ecosystems and their impact on the marine environment."

(12) For the released product, an explanatory document needs to be added to clarify the meanings of various variables and provide instructions for processing the data.

Response: Thanks for your comments. I wrote a "ReadMe.txt" file and uploaded it to Zenodo. The document is used to clarify the meanings of various variables of the dataset and provide an example of processing the data using Python code. You can choose to click the URL below to read (https://zenodo.org/record/8254335/files/ReadMe.txt?download=1).

The file contents are as follows:

The document is used to clarify the meanings of various variables of the dataset and provide an example of processing the data using Python code.
The name of each folder represents the UTC of the files inside.

Variable name	Description	Units or Type
time	The time of obtained chlorophyll–a distribution image.	'YYYYMMDD'
AE_sum	The number of anticyclonic	
CE_sum	The number of cyclonic	
predict	Prediction results in an image coordinate system derived from the deep learning model.	Array[n][7]*
eddy_type_AE0_CE1	The type of eddy (0: anticyclonic; 1: cyclonic)	Array[n]
center_lon_lat	The longitude and latitude coordinates of the eddy center pixel.	Array[n][2]
box_min_lon_lat	The longitude and latitude coordinates of the pixel in the upper left corner of the rectangular box.	Array[n][2]
box_max_lon_lat	The longitude and latitude coordinates of the pixel in	Array[n][2]

	the bottom right corner of the rectangular box.	
inradius	The radius of the circle inside the rectangular box	Array[n](meter)
internal_ellipse_area	Area of the internal ellipse of the rectangular box	Array[n](m^2)
confidence	Confidence of each eddy identification. Eddies with confidence levels below 0.2 were considered to be undesirable for data analysis.	Array[n] [0.2,1]

*Array[n][7] represents a two-dimensional array of n rows and 7 columns.
n is the sum of the number of cyclones and anticyclones.

You can perform eddy analysis by Python, or you can download other matching files such as chlorophyll, salinity, and temperature data for matching analysis.

The following example code plots the diameter distribution histograms of anticyclonic and cyclonic by the dataset.

```
import numpy as np
import glob
import pickle
import json
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
from tqdm import tqdm

geo_all = [np.array([]), np.array([])]
file_pre = 'E:\\predict\\'   # The file path needs to be changed

for i in range(8):
    str_i = '0' + str(i) + '/'

    for month in range(12):
        str_month = '0' + str(month + 1) if month < 9 else str(month + 1)
        print(i, ' ' + str_month)
        geo_dis = np.zeros((2, 5685, 5567))

        files_pre = glob.glob(file_pre + str_i + 'dataset\\????' + str_month + '??' + str_i[0:2]
+ '.json')
        for file in tqdm(files_pre):
            with open(file, 'rb') as f:
                dataset = json.load(f)
            type_index = np.array(dataset['results']['eddy_type_AE0_CE1']) == 0
            a = np.array(dataset['results']['inradius'])[type_index]
            b = np.array(dataset['results']['inradius'])[~type_index]
            geo_all[0] = np.concatenate([geo_all[0], a])
            geo_all[1] = np.concatenate([geo_all[1], b])

fig, (ax, ax2) = plt.subplots(1, 2, figsize=(5, 2), dpi=300)

```

```
plt.subplots_adjust(left=None, bottom=0.19, right=None, top=None, wspace=None, hspace=0.2)
ax2.hist(geo_all[1] / 1000 * 2, bins=np.arange(0, 100, 5), color='#000080', label='CE')
ax.hist(geo_all[0] / 1000 * 2, bins=np.arange(0, 100, 5), color='#800000', label='AE')

ax.grid(ls="--", lw=0.5, color="#4E616C")
ax.yaxis.set_major_locator(ticker.MultipleLocator(100 * 3))
ax.xaxis.set_major_locator(ticker.MultipleLocator(10))
ax.xaxis.set_minor_locator(ticker.MultipleLocator(5))
ax.xaxis.set_tick_params(length=2, labelsize=6, which='minor')
ax.xaxis.set_tick_params(length=3, labelsize=8, which='major')
ax.yaxis.set_tick_params(length=3, labelsize=8)
ax.ticklabel_format(style='sci', scilimits=(0, 1), axis='y')

ax2.grid(ls="--", lw=0.5, color="#4E616C")
ax2.yaxis.set_major_locator(ticker.MultipleLocator(1000 * 3))
ax2.xaxis.set_major_locator(ticker.MultipleLocator(10))
ax2.xaxis.set_minor_locator(ticker.MultipleLocator(5))
ax2.xaxis.set_tick_params(length=2, labelsize=6, which='minor')
ax2.xaxis.set_tick_params(length=3, labelsize=8, which='major')
ax2.yaxis.set_tick_params(length=3, labelsize=8)
ax2.ticklabel_format(style='sci', scilimits=(0, 1), axis='y')

fig.text(0.43, 0.03, 'Diameter [km]', fontsize=8)
fig.text(0.45, 0.888, '(a)', fontsize=8)
fig.text(0.872, 0.888, '(b)', fontsize=8)
plt.show()
```

(13) I strongly recommend the author to polish the language throughout the entire text, as I have identified a significant number of grammar errors and awkward expressions. The Reviewer 1 have provided many language suggestions, but it's not enough to just make changes based on those. Instead, it's advisable to seek assistance from a professional editing service for the revisions.

Response: Thanks for your comments. I took your advice and polished the whole article.

L9. 'which obtains from'. Grammatical error.

Response: Thanks for your comments. I have changed it in line 9. “which is obtained from…”

L48. 'Compared to the method of SAR images, it can …'. What does 'it' refer to?

Response: Thanks for your comments. I rephrased it as follows. “Some methods, like SAR and altimeter, only provide physical information about the ocean surface and do not capture biological or chemical processes within the eddies.” in lines 62-63.

L83. Change to 'This is conducted to avoid'.

Response: Thanks for your comments. I have corrected it.

L228. 'We counted the number of times each grid cell…'. Unclear description.

Response: Thanks for your comments. I rephrased it as follows. “We quantified the frequency of coverage for each grid cell by AEs or CEs and minimized the correlation between...”.

L320. 'ten eight-year periods'. What does this mean?

Response: Thanks for your comments. I rephrased it as follows. “We identified a total of 19,136 anticyclonic eddies and 93,897 cyclonic eddies from eight CHL images per day for ten years...”

The use of present and past tenses is confusing and inconsistent.

I can't point them all out individually. The language does not yet meet the requirements of this journal.

We feel great thanks for your professional review work on our article and for providing valuable comments. We have diligently revised and polished the entire text to ensure accurate and clear word usage, promoting a better understanding of our research. Thank you again for your review comments, we are more than willing to put in any worthwhile effort to make the article better. If you have any follow-up suggestions or guidance, we would love to hear them as well.

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