

Article

Oceanic Eddy Identification Using an AI Scheme

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Abstract: Oceanic eddies play an important role in global energy and material transport, and contribute greatly to nutrient and phytoplankton distribution. Deep learning is employed to identify oceanic eddies from sea surface height anomalies data. In order to adapt to segmentation problems for multi-scale oceanic eddies, the pyramid scene parsing network (PSPNet), which is able to satisfy the fusion of semantics and details, is applied as the core algorithm in the eddy detection methods. The results of eddies identified from this artificial intelligence (AI) method are well compared with those from a traditional vector geometry-based (VG) method. More oceanic eddies are detected by the AI algorithm than the VG method, especially for small-scale eddies. Therefore, the present study demonstrates that the AI algorithm is applicable of oceanic eddy detection. It is one of the first few of efforts to bridge AI techniques and oceanography research.

Keywords: deep learning; oceanic eddies; pyramid scene parsing network; pyramid pooling module; dilated convolution

1. Introduction

Eddies are ubiquitous oceanic features, which play an important role in global energy and material transport, and contribute greatly to nutrient and phytoplankton distribution, enhancing primary production in the ocean [1–7]. Local convergence (divergence) induced by a cyclonic (an anticyclonic) eddy due to the Coriolis effect by the Earth's rotation results in an upwelling (a downwelling) at the eddy center. The effects of eddies on the hydrological characteristics of sea water affect global heat and freshwater redistribution, and climate change. Meridional heat transport by oceanic eddies are able to supplement the heat lost at higher latitudes [2,8,9]. Cyclonic eddies bring cold water rich with nutrients and chlorophyll from the deeper layers to the surface, thus affecting the distribution of photosynthetic phytoplankton, primary production and ultimately the accumulation of fish in the eddy area [10–12]. Based on the type of oceanic data, several eddy detection algorithms have been developed to be applied to oceanic data. These methods can be divided into Eulerian methods [3,13–16], Lagrangian methods [17] and hybrid methods [18,19]. In the present study, we try to apply an artificial intelligence (AI) technology to oceanic eddy detection using satellite remote sensing measured sea surface height data.

Deep learning is one of the latest trends in machine learning in the AI field [20,21]. Deep learning methods fit the distribution of training samples (the data used to build a model) through multiple layer neural networks, which can solve the local optimal problem in traditional neural networks [20]. The most important application of deep learning is the analysis of two-dimensional images. Treating sea surface height (SSH) data as a two-dimensional image, deep learning can be applied in oceanic eddies detection. According to the demand for eddy detection, semantic segmentation can be used to identify the oceanic eddies based on the SSH data.

Lguensat et al. [22] apply a deep learning algorithm in oceanic eddies detection. Cyclonic and anticyclonic eddies are identified from the SSH data based on the encoder–decoder network U-Net in the classic framework of semantic segmentation. However, the network structure used is relatively simple. Although the scaled exponential linear units and the dice loss are used to accelerate the training and to identify eddies, quantitative characteristics of detected eddies, such as eddy sizes, are not analyzed. Subsequently, Franz et al. [23] also use the encoder–decoder network to detect and track oceanic eddies. More network parameters are applied, but only the simple convolution module and the upsampling module are stacked. Du et al. [24] use deep learning to extract higher-level features and fused multi-scale features to detect oceanic eddies automatically based on synthetic aperture radar images.

The Pyramid Scene Parsing Network (PSPNet) is able to fuse semantic and detail features in the different layers and is applicable for oceanic eddy detection due to the diversity in the distribution, sizes and shapes of oceanic eddies. The PSPNet is adopted in the present study in order to adapt the recognition of multi-scale targets.

This manuscript is arranged as follows. In Section 2, we describe the AI technique and the traditional vector geometry-based eddy detection method (VG algorithm). Section 3 introduces the data used in this study. Section 4 presents the results using the AI algorithm and the comparison with using the VG algorithm. Section 5 discusses several specific situations for the AI algorithm to detect additional eddies. Finally, Section 5 gives the summary.

2. Methods

2.1. AI Technique

2.1.1. Deep Residual Net

The neural network model used in this study is based on Deep Residual Net (ResNet) [25], which can better train in the deeper layers of the neural network. The depth of the learning network has a significant influence on the effect of classification and recognition. Deepening the network promotes learning. However, deepening of the network based on the stacking of the conventional network results in the disappearance of the gradient and leads to ineffective training. Shortcut connections are applied to the ResNet to solve the degradation problem and to obtain accuracy gains when the depth increases. A series of sensitive experiments performed by He et al. [25] show that a 101-layer ResNet can keep high complexity and can provide significant accuracy gains. Thus, a 101-layer ResNet is used for its significant learning ability in oceanic eddies detection.

2.1.2. Pyramid Scene Parsing Network

The PSPNet [26] incorporates the pyramid pooling module and the reduced convolution, which can make full use of the global scene to capture more details of the context information between the different category labels.

Information from different sub-regions can be efficiently fused with the pyramid pooling module [27,28]. In this study, four different pyramid scales are applied to fuse features in the module. To create a single bin output, the coarsest level is the global pooling. The following pyramid level divides the feature map into different sub-regions and generates pooled representation for

different locations. In order to maintain the weight of the global feature, different size convolution layers are applied after each pyramid level, decreasing the dimension of context representation to $1/N$ of the original (where N is the level size of the pyramid). Then, the low-dimension feature maps are up-sampled to obtain the same size features as the original. Finally, different feature levels are combined as the pyramid pooling global feature. The number of pyramid levels and the size of each level can be adjusted. In this study, a four-level pyramid pooling module with bin sizes of 1×1 , 2×2 , 3×3 and 6×6 grids, respectively, is applied.

Dilated convolution [28] can expand the receptive field without losing the size of feature layers. Multi-scale context features can be obtained from the dilated convolution to a feature layer with different dilation factors. Features extracted at different sampling rates are post-processed and fused separately to produce the final result. The dilated convolution is able to complete the basic network structure and to capture more global information of the images, hence optimizing the image semantic segmentation.

Sea surface height anomalies (SSHA) data labeled with eddy information are used as the training data. Figure 1 shows the configuration of the PSPNet. A 101-level ResNet (ResNet101) model with a dilated network strategy [29,30] is implemented to an input SSHA image to extract the feature map at different levels. The final feature map is reduced to $1/8$ of the input image. The pyramid pooling module is then employed to obtain context information. A four-level pyramid fuses the images at the different sizes as the global prior. The prior is connected to the original feature and a convolution layer to generate the final prediction. The PSPNet program, which is proposed by Zhao et al. [26], is publicly available and it can be obtained from <https://github.com/hszhao/PSPNet>.

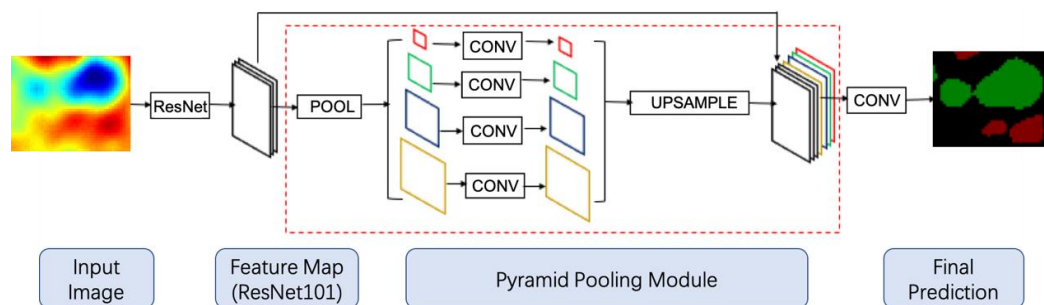


Figure 1. Schematic diagram of the Pyramid Scene Parsing Network (PSPNet). Given an input sea surface height anomalies (SSHA) image, a 101-level Deep Residual Net (ResNet) (ResNet101) model with a dilated network strategy is used to obtain the feature map of the last convolution (CONV) layer. A pyramid pooling module is then applied to gather different sub-region representations, followed by up-sampling and concatenation of layers to form the final feature representation. Lastly, the representation is passed through a convolution layer to get the final per-pixel prediction.

2.2. Vector Geometry-Based Eddy Detection Algorithm (VG Algorithm)

An automated algorithm based on the geometry of velocity vectors of the flow field [14,31] is used to identify and track mesoscale eddies from geostrophic current velocity data. The geostrophic current is calculated from SSHA. Eddy centers are determined by four criteria as follows [14]: (i) along an east–west section, meridional velocity, v , has to reverse in sign across the eddy center and its magnitude has to increase away from it; (ii) along a north–south section, zonal velocity, u , has to reverse in sign across the eddy center and its magnitude has to increase away from it: the sense of rotation has to be the same as for v ; (iii) velocity magnitude has a local minimum at the eddy center; and (iv) around the eddy center, the directions of the velocity vectors have to change with a constant sense of rotation and the directions of two neighboring velocity vectors have to lay within the same or two adjacent quadrants. Eddy sizes are computed from closed contours of the stream function field. Eddy tracks are retrieved by comparing the distribution of eddy centers at successive time steps. The tracking method for PSPNet is the same as that for VG. The tracking method is one part of the VG, which can be found in Nencioli et al. [14].

3. Data

Eddies are identified from daily SSHA data with a spatial resolution of $1/4^\circ \times 1/4^\circ$. The data, obtained from Copernicus Marine Environment Monitoring Service (CMEMS, <http://marine.copernicus.eu>), is a global product from multiple satellite altimeter along-track data. The SSHA data in the period from 2011 to 2015 are used in this study. The SSHA data are linearly interpolated into $1/8^\circ$ to make the eddy field extend for a larger number of grid points in order to further improve the performance of the eddy detection scheme [32]. The SSHA data from 2011 to 2014 are used as the training data containing the labels of eddy information, while the 2015 data are used as the validation set.

This study focuses on the North Pacific Subtropical Countercurrent (STCC, $15^\circ\text{N}\sim 30^\circ\text{N}$, $115^\circ\text{E}\sim 150^\circ\text{W}$), covering the area from east of the Luzon Strait to the Hawaii Islands, as shown in Figure 2. As an example, Figure 2 shows a snapshot of eddy distribution detected by the VG scheme.

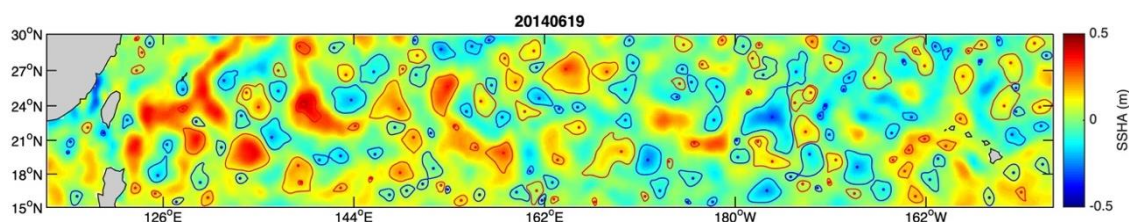


Figure 2. Oceanic eddies detected using the vector geometry-based (VG) algorithm in the North Pacific Subtropical Countercurrent (STCC) region on 19 June 2014. Blue and red curves represent cyclonic and anticyclonic eddies, respectively.

4. Results

Using the VG algorithm, the training SSHA data from 2011 to 2014 are labeled with cyclonic and anticyclonic eddy boundaries. The eddy information is then cleaned to ensure data validity and consistency. The PSPNet algorithm is applied to the training dataset for deep learning and to the validation dataset for eddy detection and information extraction.

Figure 3 shows the oceanic eddies detected in the STCC region on 15 February 2015 using the VG algorithm and the PSPNet algorithm. Oceanic eddies (392) are identified by the AI-based method, including 136 cyclonic and 256 anticyclonic eddies. More oceanic eddies are detected based on the PSPNet algorithm than that from the VG algorithm (348 eddies, 117 cyclonic and 231 anticyclonic eddies). Compared to the detected eddies in Figure 3a, more small eddies are identified by the PSPNet algorithm in Figure 3b.

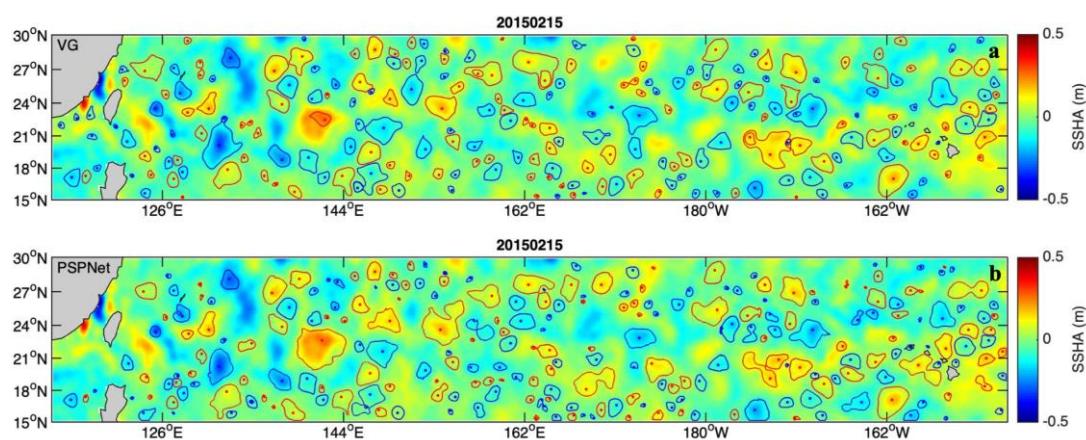


Figure 3. Comparison of the oceanic eddies detected by the two different algorithms in the STCC region on 15 February 2015. (a) Oceanic eddies detected by the VG algorithm; (b) Oceanic eddies detected by the PSPNet algorithm. Blue and red curves represent cyclonic and anticyclonic eddies, respectively.

The number of oceanic eddies detected by the two methods in the STCC region in 2015 are compared (Figure 4). During the one-year period, a total of 77462 oceanic eddies are identified by the PSPNet algorithm against a total of 68010 eddies identified by the VG algorithm. The numbers of cyclonic and anticyclonic eddies detected by the former method are both more than those detected by the latter method. Furthermore, it is observed that all the numbers of the daily eddies detected by the PSPNet algorithm are larger than that based on the VG algorithm, except on a few days in October and November (see the circled areas in Figure 4). Compared with the traditional detection results, the average eddy number from the PSPNet algorithm is about 25.90 more per day. The maximum difference between the two results is 64 eddies, and the relative error is about 13.83%. The daily eddy numbers from the two methods show a good correlation, with a correlation coefficient of 0.93. In addition, the difference between the results by the VG and the PSPNet algorithms is also characterized by seasonal variability with a reduction in the difference during November and December.

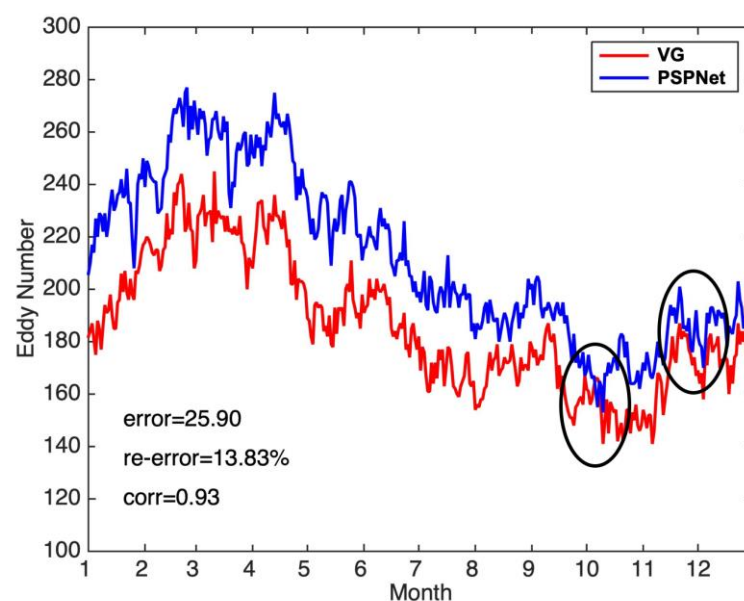


Figure 4. Comparison of the daily number of eddies detected by the two different methods in the STCC region during 2015. Red and blue curves represent the results by the vector geometry and the PSPNet algorithm, respectively. “error” is the difference between the results from the PSPNet and VG algorithms, “re-error” is the relative error which is defined as the error divided by the VG results, and “corr” is the correlation coefficient between the results from the PSPNet and VG algorithms. The circled areas are where the number of eddies detected by the PSPNet algorithm is smaller than that by the VG algorithm.

The radii of the detected oceanic eddies are also analyzed (Figure 5). The histograms of the eddy radii detected by the two methods present with a similar distribution. Both the VG-based and PSPNet-based results have peaks at the bin of 25–50 km. On the one hand, the number of eddies with the radii less than 25 km identified by the deep learning-based algorithm is more than three times of that detected by the VG algorithm. The PSPNet algorithm has an advantage in small-scale eddy (radius less than 25 km) detection. On the other hand, the PSPNet algorithm detects more big eddies than the traditional method in almost every radius bin greater than 75 km.

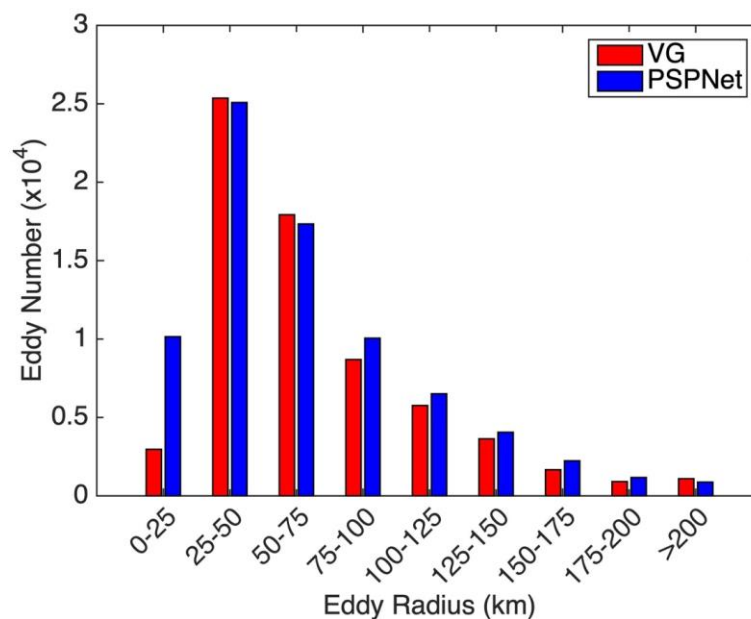


Figure 5. Radius distribution of the eddies detected by the two different methods in the STCC region during 2015. Red and blue bars represent the results by the VG and PSPNet algorithms, respectively.

Since the greatest difference between the results from the two algorithms is located for small size eddy detection, the results of detected eddies with radii less than 20 km are removed and the comparison between the two algorithms is plotted in Figure 6. The VG and PSPNet algorithms then identified 66956 eddies and 69318 eddies, respectively. The differences between the two results decrease with a similar pattern during 2015. It is suggested that the majority of the additional eddies detected by the PSPNet algorithm are small-scale. For small-scale eddies, the number of eddies identified by the AI-based algorithm is slightly more than that by the vector geometry-based algorithm. On average, 6.47 more eddies are identified per day with a relative error of 3.49%. In addition, the difference between the results provided by these two algorithms is also characterized by seasonal variability with a reduction of the difference after August.

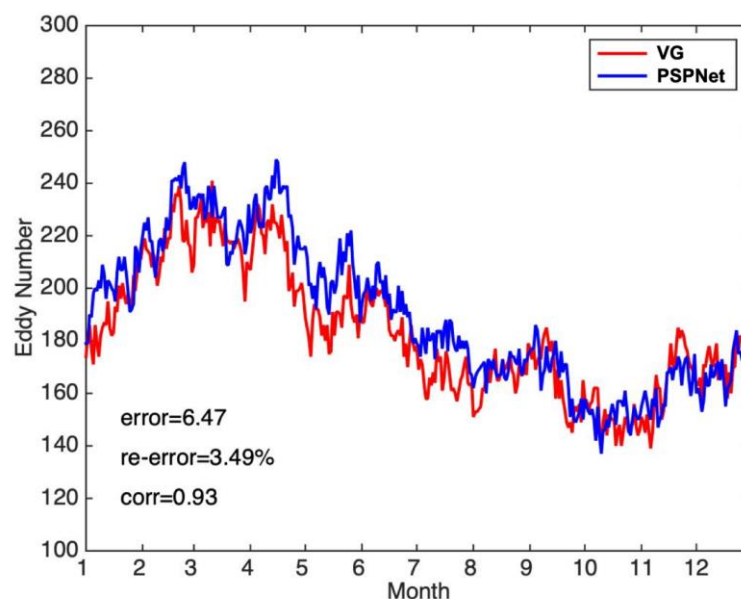


Figure 6. Same as Figure 4 except for the comparison of the daily number of eddies with radii greater than 20 km.

The lifetime of an eddy is another important parameter to characterize. Figure 7 shows the lifetime distributions of the eddies detected by the two different algorithms. From the PSPNet-detected eddies, there are 875 eddies with lifetimes greater than four weeks, including 475 cyclonic and 400 anticyclonic eddies; while 844 eddies with lifetimes greater than four weeks are detected by the VG algorithm (387 cyclonic and 457 anticyclonic eddies). Both results show that cyclonic eddies tend to live shorter than anticyclonic eddies. Furthermore, the eddies detected by the PSPNet algorithm have longer lifetimes because the AI-based method can detect small-size eddies (an eddy tends to be small during its growing and decaying periods). The longest eddy lifetime of eddies (both cyclonic and anticyclonic ones) detected by the deep learning-based algorithm is more than 30 weeks. It can better represent the whole dynamic processes of the eddies.

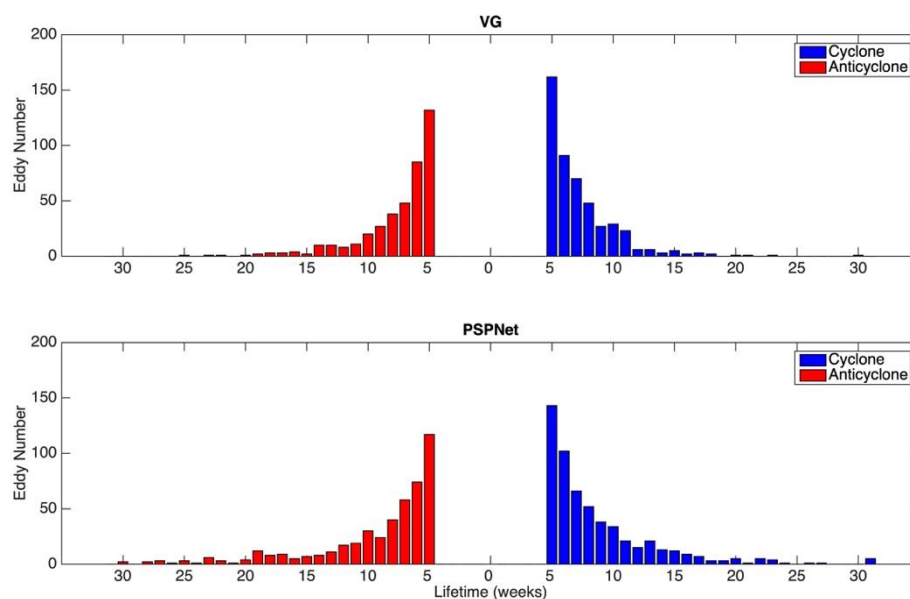


Figure 7. Lifetime distribution of the eddies detected by (up) VG and (down) PSPNet algorithms in the STCC region during 2015. Red and blue bars represent cyclones and anticyclones, respectively.

The mesoscale eddy trajectory atlas product (Version 2.0), which is obtained from AVISO+ (<https://www.aviso.altimetry.fr/en/data/products/value-added-products/global-mesoscale-eddy-trajectory-product.html>), is applied to compare with the eddies detected by the PSPNet algorithm and the VG algorithm in the STCC region during 2015. Since the AVISO+ product provides the eddies with lifetimes longer than four weeks but without boundary information (only radius), only the center locations of the eddies with lifetimes longer than four weeks in the STCC region on 7 June 2015 are plotted in Figure 8 for the comparison of the results from the three versions. The PSPNet algorithm detects the most oceanic eddies (178 eddies) of the three versions, followed by 142 eddies for the AVISO+ version and 140 eddies for the VG version. During the one year period, a total of 637 eddy tracks (including 334 cyclones and 303 anticyclones) are obtained from the AVISO product, all of which have lifetimes longer than four weeks. The PSPNet algorithm detects 875 eddy tracks with lifetimes longer than four weeks (including 475 cyclones and 400 anticyclones), while 844 tracks (including 457 and 387 anticyclones) by the VG algorithm. The number of eddy tracks from the AVISO+ version is smaller than those from the other two versions.

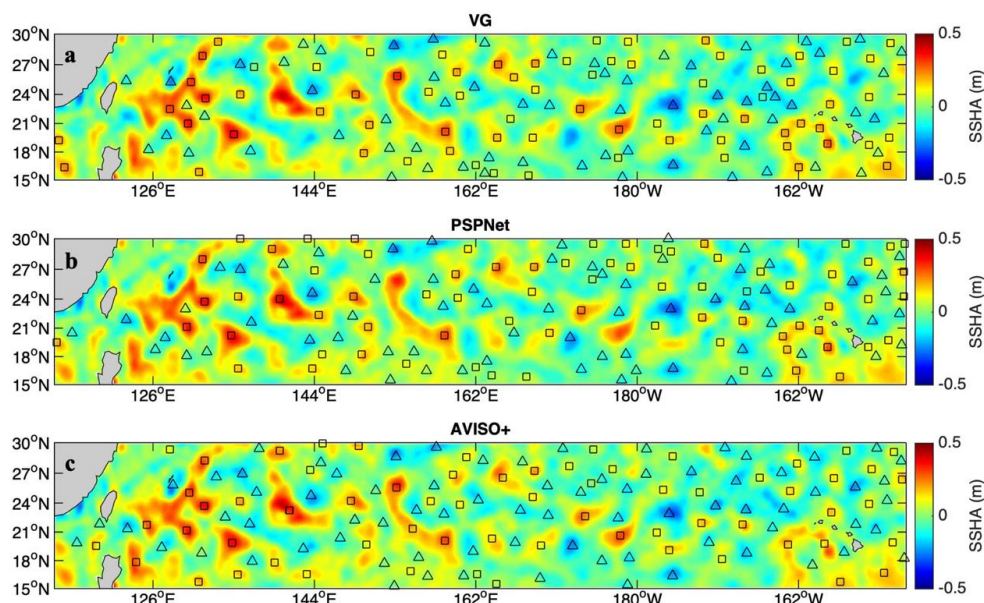


Figure 8. Comparison of the oceanic eddies with lifetimes longer than four weeks from the three algorithm versions in the STCC region on 7 June 2015. (a) Oceanic eddies from the VG version; (b) oceanic eddies from the PSPNet version; (c) oceanic eddies from the AVISO+ version. Triangles and squares represent the center of cyclonic and anticyclonic eddies, respectively.

Several eddy parameters are compared among these three results in Table 1. The mean lifetime of eddies identified by the PSPNet algorithm is shorter than that from the AVISO+ version but longer than that detected by the VG algorithm. The eddies from the AVISO+ version and the PSPNet version survive for up to a year. The mean amplitudes of the eddies from the three versions are similar, but the maximum amplitude of the eddies from the PSPNet version reaches 45.40 cm. The mean radii of the eddies from the PSPNet version, the VG version and the AVISO+ version are 90.63 km, 80.91 km and 99.58 km, respectively. The maximum eddy radii are all larger than 260 km (even close to 300 km) for the three versions. The mean displacements of the eddies from the PSPNet version and the VG version are both shorter than that from the AVISO+ version. However, the eddies from the PSPNet version and the AVISO+ version move up to more than 3000 km. Furthermore, the eddies from the three versions propagate with the similar mean speed of about 7 km per day.

Table 1. Comparisons of eddy properties base on PSPNet results, VG results and AVISO+ results.

	PSPNet		VG		AVISO+	
	Mean	Maximum	Mean	Maximum	Mean	Maximum
Lifetime (days)	62.36	346	49.15	222	71.23	364
Amplitude (cm)	8.30	45.40	7.15	40.17	8.00	34.25
Radius (km)	90.63	297.57	80.91	298.65	99.58	267
Displacement (km)	343.74	3174.0	332.22	1453.7	544.52	3355.3
Translational Speed (km/day)	6.78	34.91	6.74	24.99	6.94	34.98

In summary, the eddies detected by the VG algorithm and the AVISO+ version are similar, which demonstrate the eddy dataset the present study uses is of good quality to train the AI scheme.

5. Discussion

Comparisons of the results from the two methods show that the PSPNet algorithm can detect more eddies than the VG algorithm. According to the above analysis, most of the eddies identified by the PSPNet algorithm only are small-size eddies. There are three specific situations for the PSPNet algorithm to detect additional eddies:

5.1. Missed Eddy

Figure 9 presents the PSPNet algorithm successfully identifying oceanic eddies which are missed by the VG algorithm. On 18 July 2015, there is an area with local lower SSHA which is not identified as an eddy by the VG algorithm (Figure 9a). However, it is detected as a cyclonic eddy by the PSPNet algorithm (Figure 9b), which can also be identified from the geostrophic currents (Figure 9c). Figure 9d–f shows similar areas with local lower SSHA and local higher SSHA on 5 May 2015. The PSPNet algorithm identifies the cyclonic and anticyclonic eddies in the corresponding regions, which can be validated from the geostrophic currents.

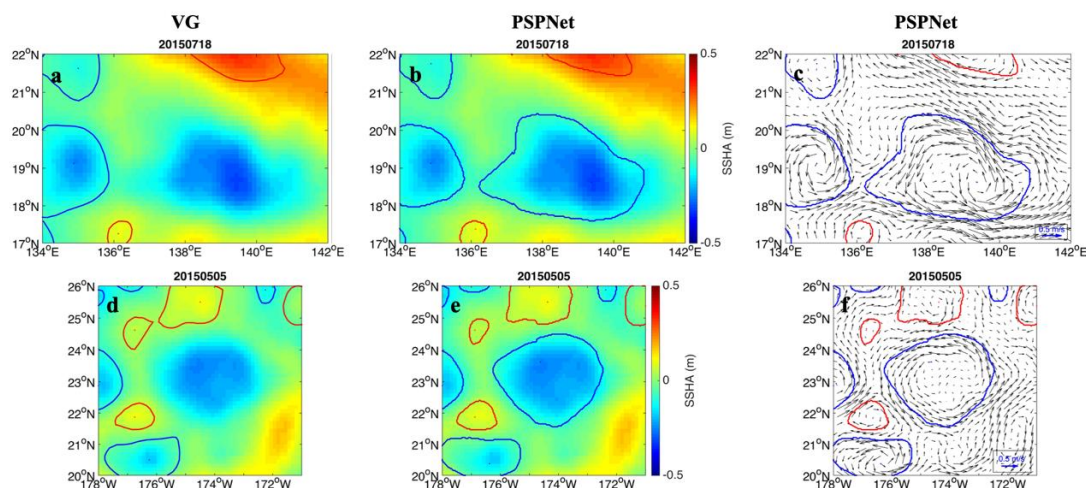


Figure 9. Comparisons of eddies on 18 July 2015 (a–c) and 5 May 2015 (d–f), which are identified by the two methods. Left column is the results by the VG algorithm labeled with SSHA data, middle column is the results by the PSPNet algorithm labeled with SSHA data, right column is the results by the PSPNet algorithm labeled with the geostrophic currents. Blue and red curves represent cyclonic and anticyclonic eddies, respectively.

In the VG algorithm, eddy centers are determined by four criteria for the spatial characteristics of the velocity fields (see Section 2.2). Distinctive velocity minimums cannot be found inside the eddies in Figure 9c,f. Thus, these two cyclonic eddies are missed by the VG algorithm in Figure 9a,d. However, they are identified by the PSPNet algorithm, which is based on the semantics of the SSHA data.

5.2. Overestimated Eddy

In the VG algorithm, the maximum closed streamfunction curve is defined as the boundary of a detected eddy, so the eddy area may be overestimated and may include several eddy centers. From the eddies identified by the VG algorithm on 23 February 2015 and 7 June 2015, shown in Figure 10a,d we found that there are two SSHA maximums inside the eddy boundaries. Using the PSPNet algorithm, the overestimated eddies are divided into several smaller ones (Figure 10b,e), which are more consistent with the geostrophic currents (Figure 10c,d).

5.3. Boundary Eddy

Due to the data selection, sometimes a half eddy appears at the edge of the study area. The closed streamfunction curve cannot be found based on the VG algorithm. Thus, a half eddy is not able to be identified by the conventional algorithm (Figure 11a,d). However, the PSPNet algorithm combines the global and detail feature information for oceanic eddy identification, and eddies can be detected with incomplete information using the AI-based method (Figure 11b,e), which can also be validated from the geostrophic currents (Figure 11c,f).

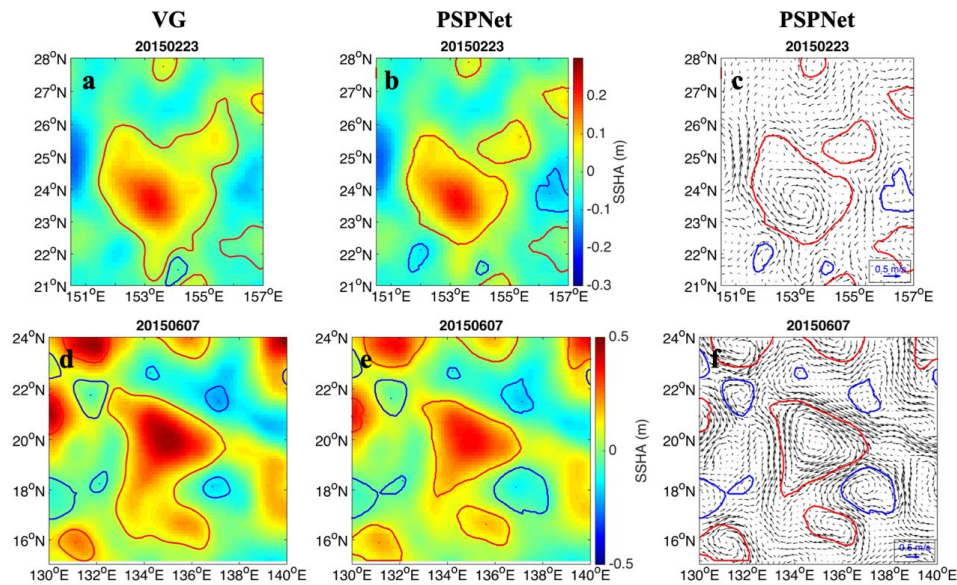


Figure 10. Comparisons of eddies on 23 February 2015 (a–c) and 7 June 2015 (d–f), which are identified by the two methods. Left column is the results by the VG algorithm labeled with SSHA data, middle column is the results by the PSPNet algorithm labeled with SSHA data, right column is the results by the PSPNet algorithm labeled with the geostrophic currents. Blue and red curves represent cyclonic and anticyclonic eddies, respectively.

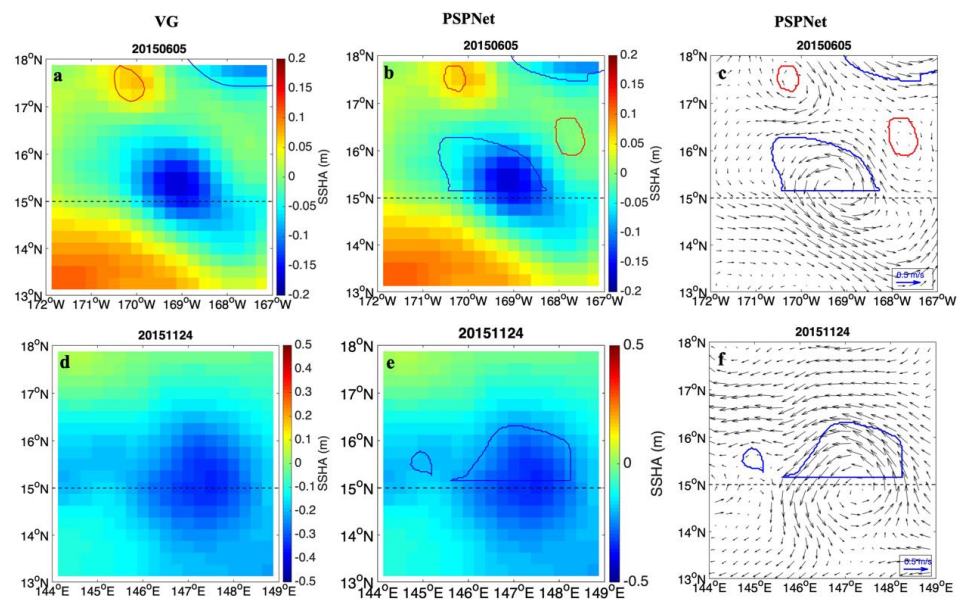


Figure 11. Comparisons of eddies on 5 June 2015 (a–c) and 24 November 2015 (d–f), which are identified by the two methods. Left column is the results by the VG algorithm labeled with SSHA data, middle column is the results by the PSPNet algorithm labeled with SSHA data, right column is the results by the PSPNet algorithm labeled with the geostrophic currents. Blue and red curves represent cyclonic and anticyclonic eddies, respectively. Black dashed lines denote the boundary of the selected data fields.

The criteria in the VG algorithm have strict requirements for the structures and patterns of the currents, which make oceanic eddies without significant features undetectable. In this study, we did not set many constraints for the AI-based algorithm. Thus, more oceanic eddies with short lifetimes or with no obvious feature information are also identified by the PSPNet algorithm.

6. Conclusions

The PSPNet algorithm, which includes a pyramid pooling module and dilated convolution, not only fuses semantic and detail features at different levels, but also captures more global and local information of the images. Therefore, the PSPNet algorithm is applicable for oceanic eddies detection. In this study, SSHA data from 2011 to 2014 with the label of eddy information extracted by the VG algorithm in the STCC region are used as the training data, and SSHA data in 2015 are used for the validation dataset. The results of eddies identified from this AI-based method are well compared with those using the traditional VG algorithm. The PSPNet algorithm is able to detect more oceanic eddies than the VG method, especially for small-scale eddies. There are three specific scenarios where only the PSPNet algorithm detects additional eddies. Therefore, the PSPNet algorithm is applicable to oceanic eddy detection, which has significant implications for the AI technique to be applied into physical oceanography studies. This AI-based eddy detection algorithm can be applied in other oceanic regions, not only in the current study area. The AI-based algorithms can also be applied to identify more physical features, i.e., oceanic fronts, internal waves and ship wakes, from different marine data.

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