Global ocean wave analysis based on the 10-year ENVISAT/ASAR wave mode data

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Abstract. The Synthetic Aperture Radar (SAR) Wave Mode (WM) is an imaging mode dedicated to ocean surface wave observation. Since the first used in the ERS-1/SAR in 1991, this imaging mode has been continuously acquired by ERS-2, ENVISAT/ASAR, Sentinel-1A/1B and the GaoFen-3, and has been providing ocean wave observation data for almost 30 years. As the Envisat/ASAR has the longest archived WM data, we used a parametric model named CWAVE_ENV to retrieve ocean wave parameters of significant wave height (SWH) and mean wave period (MWP) from all the ASAR WM data in its lifetime from December 2002 to April 2012. By comparing with the ECMWF and NDBC buoy data, we found good agreements between the ASAR retrieved results and the buoy measurements. The retrieved ASAR integral wave parameters are further calibrated using the buoy measurements based on the Reduced Majored Axes (RMA) regression method. By calibration, the bias of SWH and MWP are improved from -0.06 m to 0.00 m and from -0.19 s to 0.00 s. Cross-validation of the calibrated ASAR wave parameters with the JASON-1 Radar Altimeter SWH also shows a good consistency, with the correlation coefficient of 0.93, the bias and RMSE of 0.18 m and 0.53 m, respectively. The proposed 10-year global wave product could be a good complementary to the Radar Altimeter product and possible good dataset for wave climate study. A preliminary result of using these data for global wave analysis is shown as well in this paper.

1. Introduction
Ocean wave is a key element of dynamic marine environment, which plays an important role in interaction of ocean-atmosphere-land. Some evidences have also shown that the changes of ocean waves can also influence the climate [1]. The traditional ocean wave observations by ship and buoy consume a lot of manpower and materials. What’s more, as limited by the environment and weather, the observation data distribute inhomogeneous in spatial [2]. With the development of satellite remote sensing techniques, the ocean wave observation data volume increases rapidly. By means of space-borne active microwave sensors, such as the Rada Altimeter (RA) and the Synthetic Aperture Radar (SAR), ocean waves are measured in global ocean independent sunlight and weather conditions. By measuring the distance to the sea surface in nadir, RA is available to measure significant wave height and has been providing global ocean wave significant wave height data over 30 years [3]. Different from RA, the SAR records the radar backscatter (relevant to the roughness of sea surface) of sea surface in side-look and can provide two-dimensional ocean surface images.

The Wave Mode (WM), a SAR imaging mode dedicated to ocean observation, was first deployed in the ERS-1 mission starting from 1991 and continued in the missions of ERS-2, Envisat/ASAR and ongoing Sentinel-1A/1B, as well as the first Chinese civil SAR satellite GaoFen-3. Therefore, the SAR WM data has been available for providing ocean wave observation for almost 30 years [4-5]. The WM data are small images of approximately 5 km (azimuth) by 10 km (range), which are thus also called “imagettes”. The imagettes are acquired along the track at spatial distance of 100km for ASAR and 200 km for ERS-1,2/SAR. Though spatial coverage of these imagettes is small compared with other imaging modes, the unique advantage of SAR WM data is they are continuously acquired over global oceans.

However, to retrieve ocean wave information from SAR image is rather complicated, as the imaging of ocean waves by SAR is generally a nonlinear process [6-7]. Because the sea surface is moving during the imaging time of SAR (moving as well to synthetize a large aperture), the Doppler effect occurs to the radar signal and results in high-frequency information losing as well as image distortion. To compensate the lost information and distortion of ocean surface waves imaged by SAR, a prior information such as ocean wave spectrum obtained from numerical wave model (e.g. the WAM model [8]), called the first guess spectrum, are introduced [9-10] in the retrieval of ocean wave spectrum from SAR data. Though the full directional ocean wave spectrum could be derived by nonlinear methods, it has to depend on the prior information. By degrading the nonlinear imaging process, a quasi-linear retrieval method that needs no prior information was proposed and was used for generating ASAR WM Level2 product [11-12], which yields to retrieval of swell spectrum, probably more accurately, of ocean wave components imaged by SAR. Alternatively, parametric methods can derive directly integral wave parameters, e.g. SWH and mean wave period, from SAR images needing no prior information during retrieval. But different from the quasi-linear retrieval method, this method derives the full sea state parameters by establishing relations between radar backscatter and other parameters of SAR images and ocean wave parameters [13-15].

Though many retrieval methods have been proposed, few operational global SAR ocean wave products are available. Thus, we intend to develop a new long-term global ocean wave product based on ASAR WM data using the parametric model CWAVE_ENV, which can contribute to the basic
theory research work, and improve the performance of numerical wave model, as well as provide new evidences of long-time scale or macroscopic phenomena.

2. Dataset

2.1. ASAR WM data

In this study, the used ASAR WM data were acquired during December, 2002 – April, 2012, which are all the available data during its lifetime from March, 2002 to May, 2012. The ASAR WM data were acquired every 100 km along the track with image coverage ranging from 6 km x 5 km to 10 km x 5 km. The ASAR WM data, provided in single complex format (i.e., real part \( R_e \) and imaginary part \( I_m \)), record both magnitude and phase information of the returned radar signals, therefore the SAR image intensity (\( I \)) could be calculated as \( I = R_e^2 + I_m^2 \). By applying the provided calibration factor, the normalized radar cross section \( \sigma_0 \) is obtained and then is used for sea state parameter retrieval.

![Examples of ENVISAT/ASAR WM data](image)

**Figure 1.** Examples of ENVISAT/ASAR WM data

2.2. In situ buoy Data

In this paper, in situ buoy datasets are used to validate and calibrate the ASAR derived SWH and WMP. We collected data from 649 buoys data collected by the ECMWF and 252 NDBC buoys from the GlobWave project [16] during the period of Dec. 2002 to Apr. 2012. In situ measurements of SWH
are from the ECMWF buoy data. However, the EMCWF buoy data of “mean wave period” is the averaged of all wave period records in a certain time, while the ASAR derived MWP is the up-crossing wave period (denote $ASAR_{T_{m02}}$). Therefore, we used the NDBC buoy spectrum data to calculate the up-crossing wave period (denote $NDBC_{T_{m02}}$) according to the equation (1)-(2), and then to validate and calibrate $ASAR_{T_{m02}}$.

\[
T_{m02} = \sqrt{\frac{m_0}{m_2}} 
\]

\[
m_n = \sum_i f_i^n s_i \Delta f_i 
\]

### 2.3. RA Data

The RA SWH data used in this study is the JASON-1 SWH data, which are also accessed from the GlobWave data portal. The JASON-1 SWH data are used for cross-validation with the ASAR derived SWH (denoted $ASAR_{H_s}$). The time span of collected JASON-1 data is from December 2002 to December 2011, which is slightly shorter than the period of ASAR WM data, as we found some JASON-1 SWH data are spurious in 2012.

### 3. Methodology

#### 3.1. CWAVE_ENV parametric model

The CWAVE_ENV parametric model [14] was used to derive integral wave parameters from the ASAR WM data, which was proposed following the principle of parametric model developed for the ERS-2 SAR reprocessed WM data[13]. As development of preliminary validation of the algorithms have been elaborately described in the previous papers, no further description is given here.

Before applying the parametric model to the ASAR WM data, one should notice that some phenomena that are not related with ocean surface waves, such as oil spill, atmospheric feature and bright targets presenting in ASAR imagettes can influence the retrieved results. To ensure ‘purity’ of data, we used the ‘homogeneity parameter’ [17] for quality control of the ASAR WM data. ASAR imagettes with the homogeneity parameter greater than 1.05 are excluded from processing. Furthermore, some ASAR WM data were acquired experimentally with HH (Horizontal-Horizontal) polarization or with incident angle of 33° are also excluded from processing. After the pre-processing, there are approximately 6.48 million ASAR imagettes are available for producing global ocean wave parameters.

#### 3.2. Validation and calibration

The more than 6 million ASAR retrieved data were collocated with in situ buoy measurements and RA data for validation and calibration. The collocation criteria of ASAR with in situ buoys are the spatial distance less than 100 km and the temporal difference less than 0.5 h, respectively. The range of SWH is limited from 0.5 m to 30 m and the MWP’s from 2 s to 20 s for comparison. Eventually, there are 29,123 pairs of SWH data and 15,393 pairs of MWP data were collocated with in situ buoys. Comparisons of the ASAR derived SWH and MWP with the in situ buoy measurements are shown in
the diagrams presented in Figure 2 (a) and (b), respectively, where the colour presents the density of data pairs.

![Figure 2](image.jpg)

**Figure 2.** (a) Comparison between the ASAR-derived SWH and the ECMWF buoy data. (b) Comparison between the ASAR-derived MWP and the NDBC buoy data

From the figure 2 (a) we can see that the ASAR-derived SWH has a good agreement with the buoy measurements with the correlation coefficient of 0.89. The bias and RMSE are of -0.07 m and 0.62 m, respectively, which are close to the results of previous validation based on two-month dataset. The S.I. of 25.68% is rather higher, which maybe because that the ECMWF buoy measurements are provided by hourly while the ASAR data were acquired instantaneously. As shown in the Figure 1 (b), the ASAR-derived MWP also has a good consistency with the buoy measurements with the correlation coefficient of 0.83. The bias and the RMSE of -0.21s and 0.79s, respectively, and the S.I. is only 12.36%.

Though the ASAR-derived results generally have good agreements with the buoy measurements, the ASAR-derived SWH is overestimated in the range where the SWH is lower than 2.5m, and turns to be underestimated with the increasing of SWH. The similar trend could also be found in Figure 1 (b), where the ASAR-derived MWP is overestimated when the MWP is lower than 7s. Comparisons of the ASAR derived SWH and MWP with buoy measurements suggest that the retrieval results have rooms of improvement. Therefore, we further used the buoy measurements to calibrate the ASAR retrieved sea state parameters.

The Reduce Major Axis (RMA) regression[18-19] method is used to calibrate the ASAR retrievals. As the buoy data are not totally free of errors[20], the RMA regression method could take account into errors both from buoy measurements and ASAR retrievals. To avoid influences induced by outliers for building up the calibration, we applied the Tukey fences [21] and the Robust Regression method[22] to the collocation data pairs to remove outliers. The definition of Tukey fences is shown below.
\[IQR = Q3 - Q1\]
\[lower \ fence = Q1 - 1.5IQR\]
\[Upper \ fence = Q3 + 1.5IQR\]

Where, the Q1, Q2 and Q3 represent the first, second and third quartiles, respectively. The Q1 divides data into the first 25% and rest 75%. The Q3 divides them to the first 75% and the last 25% and the Q2 is the median of data. The IQR is the difference between Q3 and Q1. The data smaller than lower fence or less than higher fence are detected as outliers. The Robust Regression is insensitive to outliers, as it can assign data with different weight during iterations. The bigger the residual is, the smaller the weight will be assigned in the next iteration of regression. In this paper, we used 0.15 as the threshold of weight and the collocation data pairs with weights lower than 0.15 are marked as outliers. By applying the Tukey fences and the Robust regression method, 1034 SWH data and 423 MWP data are detected as outliers, respectively. Eventually, 28,089 pairs of SWH data and 14,970 pairs of MWP data were collected. The Figure 3 (a) and (c) show the scatter diagrams of ASAR-derived SWH and MWP against the buoy measurements after removing outlier, where the cross signs represent the detected outliers. By applying the RMA regression method, the calibrate formula is derived as follows.

\[Calibrated_{ASAR \_H_e} = 1.140 \times ASAR \_H_s - 0.402\] (4)

\[Calibrated_{ASAR \_Tm02} = 1.268 \times ASAR \_Tm02 - 1.887\] (5)
Figure 3. (a) Comparison of ASAR-derived SWH against the buoy measurements. (b) Comparison of the calibrated ASAR-derived SWH against the buoy measurement. (c) Comparison of ASAR-derived MWP against the buoy measurement. (d) Comparison of the calibrated ASAR-derived MWP against the buoy measurements.

As shown in the Figure 3 (b) and (d), the bias of SWH comparison is improved from -0.06 m to 0.00 m, and the bias of MWP is improved significantly from -0.19 s to 0.00 s, which suggests that the applied calibration performs well for the ASAR-retrieved wave parameters. Though other three statistical parameters are not improved after calibration, the error bars overlaid on the scatter diagrams suggest that the overestimation and underestimation of the ASAR retrievals are significantly improved, as the mean values of each bins almost lie on the 1:1 diagonal line.

Figure 4. (a) The calibrated ASAR derived SWH against the calibrated RA SWH. (b) Variations of the ASAR derived SWH Bias and RMSE along with RA SWH. The blue lines show the variations of bias and RMSE of uncalibrated ASAR-SWH and the red lines are the variations of calibrated results.
We also conducted cross-validation of the ASAR-retrieved SWH data with the calibrated RA data. Following the same collocation criteria mentioned above, 22,862 pairs of data collocated after removal of outliers using the Tukey fence. The comparison result is shown in 4 (a), from which we can see that the calibrated ASAR-derived SWH data have a good agreement with the calibrated RA measurement, with the correlation of 0.93, the RMSE of 0.53 m, the bias of 0.18 m, and the S.I. of 16.64%. Variations of the bias and the RMSE of ASAR-derived SWH compared with RA data in each bin (1 m interval) are shown in Figure 4(b). We used blue lines to represent the uncalibrated results and red for calibrated results. The solid lines and dash lines show the change of Bias and the RMSE, respectively. From the comparison, we can see that the bias and the RMSE have been improved in most part of data after calibration, except the data with SWH range from 1.5 m to 4m, where the raw ASAR retrievals have good agreements with the RA data, so the calibration is unable bring much improvement, and the differences between the calibrated SWH and uncalibrated SWH are small.

4. **Statistical analysis of global ocean waves**

Following the validation and calibration of the ASAR derived SWH and MWP, in this part, we used this 10-year global sea state parameters to conduct a preliminary analysis of global ocean wave characteristics.

As the sea ice in the polar regions may influence the retrieval of sea state parameters, the statistical analysis limits to latitudes lower than 70 degrees. The valid SWH is in the range between 0.5 m and 30 m, and the valid MWP is between 2 s and 20 s. By allocating the ASAR-derived SWH and MWP from each WM data to $2^\circ \times 2^\circ$ grids, the averaged ASAR-derived sea state parameters are calculated, as shown in the maps of Figure 5. In the left column of Figure 5 are the results of original ASAR-derived sea state parameters, while the calibrated results are shown in the right column of Figure 5.
Figure 5. Global maps of mean sea state based on the ten-year wave mode data: (a) mean SWH, (b) mean calibrated SWH, (c) mean MWP and (d) mean calibrated MWP.

Compared Figure 5 (b) to (a), one can find that the calibration increases significantly SWH in the Southern Hemisphere, particularly in the region from 60°S to 30°S, where the westerlies is dominant. The averaged of SWH increases from 3.32 m to 3.38 m after calibration, and the percentile of data greater than 4 m raises from 8.90 % to 16.42%. On the other hand, the SWH in the region from 30°S to 30°N decreases compared to results before calibration, where the ASAR-derived SWH is in relatively low sea state (lower than 2.5 m), which is used to be overestimated according to the previous validation analysis. Comparing Figure 5 (d) to (c), one can find that the calibration of MWP seems to have the similar effects of calibration on SWH, i.e. it increases in the Southern Hemisphere and decreases in the region between 30°S to 30°N, while remains nearly unchanged in the high latitude region in the Northern Hemisphere. The most distinguished feature of the MWP global maps is that the largest averaged MWP (of approximately 9 s) appears in the southwest of Australia, where long swells generated in the westerlies are concentrated.

Figure 6. Global maps of extreme sea state: (a) 99th percentile of the calibrated SWH and (b) 99th percentile of the calibrated MWP.

We further analyzed the extreme sea state based on the ten-year ASAR wave mode data by calculating the 99th percentile values of calibrated SWH and MWP, as shown in Figure 6 (a) and (b),
respectively. No surprising that the extreme SWH (of approximately 10 m) occurs in the high latitudes’ regions in the both Hemispheres, where the westerlies are dominant. Noting in the Northern Indian ocean, the 99th percentile of SWH is also high, of 6 m. Comparing the patterns of extreme MWP to those of SWH, we found it is very interesting. In the Northern Hemisphere, when the extreme SWH appears in the North Pacific and North Atlantic between 30°N and 60°N, the extreme patterns of MWP in the same region shift towards southeast beyond 30°N, indicating the extreme swell (with high MWP of approximately of 12 s) generated by North Pacific storms propagate southeast. The same feature is also observed in the Southern Hemisphere. The extreme SWH spans the 30°S and 60°S belt, while the extreme MWP clearly spans beyond 30°S further to north.

5. Summary and Conclusion

In this study, we presented the Cal/Val of the SWH and MWP based on the ten-year ASAR wave mode data. Preliminary analysis of the statistical characteristic of global ocean waves based on these data are also presented.

By comparing the ASAR-derived results with the in situ buoy data, good agreements are achieved with correlation coefficient of 0.89 and 0.83 for SWH and MWP. The RMSE and Bias of SWH comparisons are of -0.07 m and 0.62 m, respectively. The RMSE and Bias of MWP comparisons are of -0.21 s and 0.79 s, respectively. These statistical parameters are comparable with the preliminary validation results of the CWA_ENV algorithm 14, which suggests that the parametric model CWA_ENV has a good performance in retrieving ocean wave parameters from ASAR WM data.

By applying the Turkey fences and robust regression, outliers of the comparisons are removed. Then the RMA regression is applied to calibrated the ASAR retrievals using the buoy data. The Bias of ASAR-retrieved SWH and MWP are improved significantly, from -0.07m to 0.00 m and from 0.19 s to 0.00 s respectively. Though other statistical parameters remain almost unchanged, both the overestimation and underestimation trends in SWH and MWP are improved. The cross-validation of calibrated ASAR-derived SWH also shows a good consistency with the JASON-1 RA measurements, with correlation coefficient of 0.93, the Bias and RMSE is 0.18 m and 0.53m, respectively.

Based on the ten-year ASAR WM sea state parameters, we conducted the preliminary analysis of mean and extreme sea state of global ocean waves. Distinct features of mean and extreme sea state in the global oceans are found, which suggests the potential of using this dataset for further analysis.

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