Estimation of sea-level variability around the Java Sea and Karimata Strait using Cryosat-2 Altimeter

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Abstract. Sea-level rise is a big problem in the future. Indonesia is a country with the potential impacts of sea-level rise; therefore, the continuous monitoring of sea-level variability becomes urgent. Globally, sea-level rise is up to 3 mm year⁻¹ estimated by satellite altimetry data. How about the sea level rise in Indonesia, particularly in western Indonesia such as Java sea, Karimata Strait? This paper aims to estimate the sea-level rise in the western Indonesian seas, such as the Java Sea and the Karimata Strait. The estimation was derived using the Cryosat-2 altimetry data. The data used is in a period of 9 years (2010 to 2018). The trend in the period is negative 4 mm year⁻¹. The area also has a low correlation with ENSO with a value negative 0.25

1. Introduction

The changes in the sea-level over millions of years show that sea-level rise is accelerating over time. The observations based on satellite altimetry measurement, sea-level rises to 3.1 ± 0.3 mm year⁻¹ and acceleration of 0.1 mm year⁻² over 1993–present [1]. Sea-level does not rise uniformly throughout the world due to the non-uniform ocean warming and salinity [2]. The Indonesian seas have a higher trend compared the global. The study of sea-level variability in Indonesia during the period 1993-2016 indicates that the sea-level rise in Indonesia was up to 8 mm year⁻¹ [3]. The changes of sea-level are associated with El Niño Southern Oscillation (ENSO) [4,5] that dominates sea-level variability along the east and southwest sides of Pacific Ocean basins. Meanwhile, North Atlantic Oscillation (NAO) that affect the changes in the northeast Atlantic Ocean.

Since ERA-1 and TOPEX/Poseidon were launched in 1991 and 1992, respectively, the monitoring of sea level is available globally. The next mission, such as Envisat, Jason-1, Jason-2, and Jason-3 were to complete the long-term sea-level variability. Most radar altimeters use the pulse-limited mode or called Low-Resolution Mode (LRM) that transmitter emits the signal toward the sea surface, and it is received backward. This mode has the area of the reflecting surface, named footprint. In this mode, the size of the footprint is usually several kilometers. Unlike most radar altimeter, CryoSat-2 is a radar altimeter which brings the SAR Interferometer Radar Altimeter (SIRAL) instrument which can perform with a higher spatial resolution than LRM. SIRAL is designed with three operational modes that can be used for observations at sea and ice sheets, such as LRM, SAR, and SARIn [6]. The objective of the CryoSat-2 mission is to measure the extent of thinning Arctic ice due to climate change. Cryostat-2 flies in altitude at 717 km, with an inclination of 92°, and reaches latitudes of 88°. in Open Ocean, Cryosat-2 uses LRM mode, however, the mode will be changed to SAR mode when cryostat-2 through floating sea ice and land ice-sheets. Not only to monitor the thickness of the polar ice sheets and floating sea ice...
but also, Cryosat has a mission to understand the global climate change. Cryosat-2 has the equatorial inter-track distance is 7.5 km[7].

The Indonesian seas consist of about 20 (seas, gulfs, and straits), such as Java Sea, Banda Sea, Karimata Strait, Makasar Strait, and so forth. [8]. The Karimata strait around the North Natuna Sea and the Java Sea with the coordinates of 8° N to 8° LS and 102° E to 118° BT are the area of interest (AOI) of this study. This AIO is unique due to the freshwater, and low salinity from the South China Sea meet the java sea that influenced by the Indonesian Throughflow (ITF) [9,10].

The study aims to estimate sea-level variability around AOI based on Cryosat-2 altimeter data for a period 2010 to 2018 and the correlation with El Niño Southern Oscillation (ENSO).

2. Data and Methods

2.1. Data
In this study, the data of 1 Hz of Cryosat-2 were extracted from the Radar Altimeter Database System (RADS) in a period 2010 to 2018. The parameters which have to be involved in processing are satellite orbit height (altitude), altimeter height (range), measurement time, dry tropospheric correction, wet tropospheric correction, ionospheric correction, sea state bias correction, tides correction (which consists of solid tide, pole tide, ocean tide, and load tide), dynamic atmospheric correction (DAC), reference frame offset (RFO), and mean sea surface (MSS). The Multivariate ENSO Index (MEI) data are needed as well within the same period, which is an index that represents the ENSO phenomenon. MEI is based on the six main variables observed in the tropical Pacific Ocean. These variables are sea surface pressure (SLP), zonal components and surface wind meridional, sea surface temperature (SST), surface air temperature, and outgoing longwave radiation (OLR). The high value of MEI data shows the El Niño phase, while the low value of MEI represents the La Niña phase. MEI values are centred between the previous and the following month (bi-monthly) [11].

2.2. Methods
The parameters used in processing as specified in Table 1 [12].

| Parameter          | Model   | Alternative Model |
|--------------------|---------|-------------------|
| Altitude           | CNES GDR-E | CNES GDR-D, CNES |
| Range              | Ku-band | -                 |
| Dry tropospheric correction | ERA    | ECMWF             |
| Wet tropospheric correction | ERA    | ECMWF             |
| Ionospheric correction | smooth | JPL GIM           |
| SSB correction     | hybrid  | -                 |
| DAC                | MOG2D   | static            |
| Solid tide correction | tide_solid | -                 |
| Pole tide correction | tide_pole | -                 |
| Ocean tide correction | FES2014b | -                 |
| Load tide correction | FES2014b | -                 |
| MSS                | CNES-CLS15 | -                 |
| RFO                | ref_frame_offset | -               |

In the processing, some limits are applied to the parameters as the following Table 2 [12] to avoid the outliers. The coordinates of longitude and latitude data are also given the limits according to the AOI. Data containing NaN values is replaced by a value that exceeds the limit of observation data (for example = 999.9) in case it is selected during the data quality control process.
2.2.1. SLA calculation. SLA is calculated by applying the corrections. The equation to calculate the sea-level anomaly [13] is:

\[ h_{\text{SLA}} = H - R_{\text{obs}} - \Delta R_{\text{dry}} - \Delta R_{\text{wet}} - \Delta R_{\text{iono}} - \Delta R_{\text{ssb}} - h_{\text{tides}} - h_{\text{atm}} - h_{\text{MSS}} \]  \hspace{1cm} (1)

whereas \( h_{\text{SLA}} \) is a sea-level anomaly, \( H \) is the altitude, \( R_{\text{obs}} \) is the range, \( \Delta R_{\text{dry}} \) is the dry tropospheric correction, \( \Delta R_{\text{wet}} \) is the wet tropospheric correction, \( \Delta R_{\text{iono}} \) is the ionospheric correction, \( \Delta R_{\text{ssb}} \) is the sea state bias correction, \( h_{\text{tides}} \) are the sum of solid tide, pole tide, ocean tide, and load tide correction, \( h_{\text{atm}} \) is the dynamic atmospheric correction, and \( h_{\text{MSS}} \) is mean sea surface. All these variables have units of meters. The value of SLA is afterward averaged per cycle by the weighting based on latitude. The averaged SLA based on the previous and following month (bi-monthly) is also calculated due to according to the MEI data. The weight is applied to each observation value which is based on the cosine of the latitude [14].

2.2.2. Decomposition. Time series decomposition is done for cycle-averaged and bi-monthly SLA data. This process will extract the SLA raw data into seasonal, trends, and remainder components. The method used in the decomposition process is STL (a Seasonal-Trend Decomposition Procedure Based on LOESS) [15]. SLA linear trend is calculated from the trends data using linear regression according to the equation of:

\[ y = ax + b \]  \hspace{1cm} (2)

Where \( y \) is the scalar response or dependent variable, \( x \) is the regressor, predictor variable or independent variable, \( a \) is a slope of the function and line, and \( b \) is the line intercept (\( y \) value when crossing the Y-axis) [16]. Obtaining the value of the independent variable \( x \) can be done by substituting the value of the dependent variable with the year data.

2.2.3. Comparison to MEI. The comparison to MEI is made by calculating the correlation coefficient of detrended bi-monthly SLA and MEI data. Detrended SLA is obtained from subtracting the value of the SLA bi-monthly trend to the SLA value itself. This process is calculated according to equation (3). The formula shows a calculation of the correlation coefficient that is done by dividing the data covariance \( \sigma_{xy} \) by the standard deviation of the variables \( X \sigma_x \) moreover, the standard deviation of the variable \( Y \sigma_y \) [16].

\[ \rho = \frac{\sigma_{xy}}{\sigma_x\sigma_y} \]  \hspace{1cm} (3)
The value of the coefficient needs to be interpreted so that it can be convenient to evaluate the correlation of the data.

**Table 3.** The Strength of Correlation

| Value of $\rho$ | Interpretation        |
|-----------------|-----------------------|
| 0.90 to 1.00    | Very high correlation |
| 0.70 to 0.89    | High correlation       |
| 0.50 to 0.69    | Moderate correlation   |
| 0.30 to 0.49    | Low correlation        |
| 0.00 to 0.29    | Very low correlation   |

Table 3 [16] states the relation of each correlation coefficient. The correlation coefficient values range is from -1 to 1. A positive coefficient indicates a linear correlation, while a negative coefficient indicates an anti-correlation. The calculation of the correlation coefficient resulting in an exact coefficient of 0 shows that there is no correlation at all the two variables.

3. Results and Discussions

The data in the period 2010 to 2018, the highest mean SLA is in cycle 87 in 2016 with a value of 142.5 mm, while the lowest mean SLA is in cycle 70 in 2015 with a value of -93.4 mm. In the bi-monthly data, the highest mean SLA is in 2010 with a value of 162.3 mm, while the lowest mean SLA is in 2015 with a value of -92.2 mm. Figure 1 (a) shows that the inter-mean SLA for both data has a slight difference and a similar pattern every year.

![Figure 1](image-url)

**Figure 1.** (a) Mean SLA graph of CryoSat-2 and bi-monthly SLA and (b) CryoSat-2 and bi-monthly SLA trends and linear trends.

Time series decomposition process resulted in 4 graphs such as seasonal, trend, remainder, and raw data, which is the mean SLA data itself. Trend components can have a pattern of increasing or decreasing. Both of CryoSat-2 and bi-monthly data from 2010 to 2018 have a trend with a decreasing pattern and slight difference of 1.3091 mm, as shown in Figure 1 (b). The linear regression equation according to equation (2) for the CryoSat-2 trend $y = -4.0371x + 8147.6453$ and $y = -3.9751x + 8021.2993$ for the bi-monthly trend. Variable $\alpha$ for both data have negative values that evince decreasing linear trends. The seasonal graph in Figure 2 (a) and (b) show the regular repeating pattern every year.
Figure 2. Time series decomposition results; (a) CryoSat-2 data and (b) bi-monthly data.

Based on the estimation of a linear trend, the areas of the Java Sea and the Karimata Strait were getting a degradation from 2010 to 2018 by a trend of 34.2 mm. The most significant decreasing trend from 2014 to 2016 is in line with the El Niño event that occurred in the same year. El Niño in 2014-2015 is categorized at low intensity. The El Niño phenomenon arrived with intense energy in early July 2015 and lasted until early March 2016 [19]. The peak of this event with a vigorous intensity occurred in November 2015. This condition caused the surface of the Java Sea and the Karimata Strait to shrink at that time.

As in Figure 3 (a) below, the bi-monthly SLA CryoSat-2 data is represented by the green line. The red shade of the graph illustrates the positive values of MEI data based on the influence of El Niño (warm phase), while the blue shade represents the negative values based on the impact of La Niña (cold period). Generally, the graph below shows an inverse relationship between CryoSat-2 SLA data and MEI data from 2010 to 2018. As in Figure 3 (b), the red line showing a linear trend of the distribution of detrended bi-monthly SLA and the MEI data has the equation of $y = -0.0041x - 0.2376$. The negative value for variable $a$ showing a decreasing linear trend is in line with the detrended bi-monthly SLA and MEI correlation coefficient $\rho$ of -0.2503. The correlation coefficient proves an anti-correlation between the Java Sea and the Karimata Strait detrended sea-level anomaly and the MEI data from 2010 to 2018, and this correlation is very low. This is caused by the difference in the location of SLA and MEI data retrieval. MEI data are taken in the tropical Pacific Ocean region with coordinates of 30° N to 30° S and 100° E to 70° W, whereas the observation is at coordinates 8° N to 8° S and 102° E to 118° E.
ENSO, which is the dynamics of the atmosphere and the sea around the Pacific Ocean, will have an inverse impact on the area around the Indonesian Sea. During El Niño, sea-level becomes anomalously high with an increase of tens of centimeters in the eastern tropical Pacific Ocean and low in the western tropical Pacific Ocean [17]. The small surface of the Indonesian Sea can be triggered by the transfer of the through-flow during ENSO events. An increase in the flow through the South China Sea during El Niño together with an equal southward flow increase through the Sulu Sea and Sibutu Passage to the northern Makassar Strait inhibits the injection of surface waters of the Pacific Ocean so that the surface of the Indonesian Sea decreases [18]. During the La Niña phase, the intensity of the South China Sea flow to the Sibutu Passage decreases to near zero and leads the through-flow to the north. This condition allows the inflow surface water from the Pacific Ocean to the South China Sea and the Indonesian Sea with the result that the sea-level rises. This is what causes the correlation of the observational and MEI data not to be in a linear correlation.

4. Conclusions
In this study, the estimation of sea-level trends all around AOI using Cryosat-2 altimeter is performed. The trend of sea level around the interest areas (such as Karimata Straits and Java Sea) from 2010 to 2018 is negative 4 mm year\(^{-1}\). The correlation between de-trending sea level and MEI is negative 0.25. It means that ENSO does not influence too many in this area. The result agreed with the previous study [5]

5. References
[1] Group W G S L B 2018 Global sea-level budget 1993–present Earth System Science Data 10 1551-90
[2] Nicholls R J and Cazenave A 2010 Sea-level rise and its impact on coastal zones Science 328 1517-20
[3] Cazenave A and Llovel W 2010 Contemporary Sea-level Rise Ann. Rev. Mar. Sci. 2 145–73
[4] Handoko E, Fernandes M and Lázaro C 2017 Assessment of Altimetric Range and Geophysical Corrections and Mean Sea Surface Models—Impacts on Sea-level Variability around the Indonesian Seas Remote Sensing 9 1-32
[5] Brijker J M, Jung S J A, Ganssen G M, Bickert T and Kroon D 2007 ENSO related decadal-scale climate variability from the Indo-Pacific Warm Pool Earth and Planetary Science Letters 253 67-82
[6] Handoko E Y, Hariyadi and AnindyaWirasatriya 2018 The ENSO’s Influence on the Indonesian Sea Level Observed Using Satellite Altimetry 1993 - 2016 In: 2018 IEEE Asia-Pacific Conference on Geoscience, Electronics and Remote Sensing Technology (AGERS), (Jakarta: IEEE)
Laxon S W, Mallow U, Mavrocordatos C, Phalippou L, Ratier G, Rey L, Rostan F, Viau P and Wallis D W 2006 CryoSat: A mission to determine the fluctuations in Earth’s land and marine ice fields Advances in Space Research 37 841-71

[7] Jiang L, Schneider R, Andersen O and Bauer-Gottwein P 2017 CryoSat-2 Altimetry Applications over Rivers and Lakes Water 9

[7] IHO 1953 Limits of Oceans and Seas (special publication no 23) - 3rd Edition. ed I H Organization

[8] Gordon A L 2005 Oceanography of the Indonesian Seas and Their Throughflow. In: Oceanography, pp 14–27

[9] Poerbandono, Handoko E Y and Adyitia D 2018 Extremes of residual water levels in the West of Java Sea, Indonesia. In: International Symposium on Earth Hazard and Disaster Mitigation 2017, ed I Meilano, et al. (Bandung: American Institute of Physics)

[10] Mazzarella A, Giuliani A and Liritzis I 2010 On the 60-month cycle of multivariate ENSO index Theor. Appl. Climatol. 100 23–7

[11] Scharroo R 2012 RADS version 3.1 - User Manual and Format Specification. ed D NOAA

[12] Andersen O B and Scharroo R 2011 Coastal Altimetry, ed S Vignudelli, et al. (Berlin Heidelberg: Springer-Verlag) pp 103

[13] Gleisner H 2011 Latitudinal Binning and Area-Weighted Averaging of Irregularly Distributed Radio Occultation Data

[14] Cleveland R B, Cleenan W S, McRae J E and Terpenning I 1990 STL: a Seasonal-Trend Decomposition Procedure Base on Loess Journal of Official Statistics 6 3-73

[15] Asuero A G, Sayago A and Gonz A G 2006 The Correlation Coefficient : An Overview Crit. Rev. Anal. Chem. 36 41–59

[16] Church J A, White N J and Hunter J R 2006 Sea-level rise at tropical Pacific and Indian Ocean islands Glob. Planet. Change 53 155–68

[17] Gordon A L, Huber B A, Metzger E J, Susanto R D, Hurlburt H E and Adi T R 2012 South China Sea throughflow impact on the Indonesian throughflow Geophys. Res. Lett. 39 1–7