

## REGIONAL PROJECTION OF SEA LEVEL RISE: THE SETO INLAND SEA CASE IN JAPAN

Han Soo Lee<sup>1</sup>, Mai Van Cong<sup>2</sup>

**Abstract:** *The future sea level rise (SLR) in the year of 2050 and 2100 are estimated by using ensemble empirical mode decomposition (EEMD) with long-term sea level records in and around the Seto Inland Sea, Japan. Ensemble empirical mode decomposition, an adaptive data analysis method, can separate the sea level records into intrinsic mode functions (IMFs) from high to low frequency and the residue. The residue is considered as the non-linear trend from the sea level records. The SLR trend at Tokuyama in the Seto Inland Sea obtained from EEMD is 3.58 mm/yr over 1993-2010, which is slightly larger than the recent altimetry-based global rate of  $3.3 \pm 0.4$  mm/yr over 1993-2007. Then, the non-linear trend is utilized to project the regional SLR in the Seto Inland Sea. The resulting SLR in 2050 and 2100 estimated are 0.18 m and 0.49 m at Tokuyama, respectively. The SLR is not only due to mass and volume changes of sea water, but also due to other factors such as local subsidence, river discharge and sediments, and vegetation effect. The non-linear trend of SLR, which is the residue from EEMD, can be regarded as a final consequential sea level after considering those factors and their nonlinearity. The EEMD method can be useful tool not only for the SLR projection under climate change, but also for observed data analysis in coastal engineering and hydrology.*

**Keywords:** *sea level rise (SLR), ensemble empirical mode decomposition, regional projection of SLR, Seto Inland Sea.*

### 1. INTRODUCTION

Recently, it is commonly accepted that global mean sea levels have increased steadily over the past century as a result of an increase of the global mean atmospheric temperature (Cazenave and Llovel, 2009; IPCC, 2007). Continued increases in mean sea levels are predicted to have catastrophic impacts on coastal environments around the world in the coming near future.

In climate change impact studies on coastal flooding, for example, in Bangladesh which is one of the most vulnerable countries to SLR (Ali, 1996; 1999; Karim and Mimura, 2008; Rahman, 2009; Ruane et al., 2013; Sarwar, 2005), the SLR projections are adapted by simple scenarios, for instance 1 m rise by 2100, or by physical process-based dynamic

(deterministic) modeling approaches, for example a (ensemble) simulation result from the global climate models (GCMs) with high uncertainty with respect to the glaciers and ice sheet dynamics. Our limited understanding of the ice sheet dynamics and lack of long-term observations of ice sheet changes make it difficult to predict the SLR due to ice sheets contribution by process-based dynamic model (Rahmstorf, 2010). Recently, there is growing demand for regional projection of SLR for better reliable scenarios by taking not only the global mean of SLR but also the regional variations into account (Willis and Church, 2012). Moreover, the local effects such as uplifting and subsidence on the sea level change has to be considered in the regional SLR scenarios for climate change impact analysis in low-lying coastal environments (Lee, 2013). Therefore, the objective in this study is to illustrate the novel way for regional projection of SLR in the Seto Inland Sea (SIS), Japan,

---

<sup>1</sup> Graduate School for International Development and Cooperation, Hiroshima University,

<sup>2</sup> Department of Coastal Engineering, Water Resource University.

with long-term sea level records.

The SIS is a largest long channel-shaped enclosed coastal sea in the western part of Japan with a size of about 23,000 km<sup>2</sup>, a length of about 500 km and an average depth of about 38 m (Tsuge and Washida, 2003; Yamamoto, 2003; Yanagi et al., 1982). It is connected to the outer Pacific Ocean and sea via the Kii Channel, the Bungo Channel and the Kamon Strait. In addition to its mild climate and beautiful scenery of sandy beaches, tidal flats, and historical heritages, it includes approximately 1000 islands and a number of narrow waterways/straits (Seto in Japanese) connecting the basins (Nada in Japanese) and bays (**Fig. 1**). As parts of Japanese coast under frequent passes of typhoons in summer, the SIS experiences frequent storm surges (Lee et al., 2010).

In this study, we estimate the future regional SLR based on data-driven statistical modeling approach using ensemble empirical mode decomposition (EEMD) with long-term sea level records in and around the SIS, Japan. By using the EEMD, we illustrate a novel way of projecting SLR to the mid- and long-term future by the years of 2050 and 2100. In the following, observed data and analysis method used are given in Section 2. Section 3 describes the results of data analysis using EEMD. Finally, conclusions are presented in Section 4.

## 2. DATA, METHOD AND PROCEDURE

### 2.1 Data

The observed sea levels from 17 stations in and around the SIS, Japan, are obtained from Japan Meteorological Agency (JMA) and Japan Coastal Guard (JCG). The observed data periods used in this study are all different for each station. The longest hourly dataset used comprises for 61 years from January 1 1950 to December 31 2010 at Tokuyama, the Station No. 13 in **Fig. 1**. The total number of original raw data at Tokuyama is 534,720 with

intermittent missing data of total 10,915 (2.04% of complete data). The other stations also show missing data fractions less than 10% of complete data except the Kochi station with 13.34%. The observed tidal levels at all stations are referenced with respect to the Tokyo Peil (TP) of Japan. In the analyses, the predicted tides for the missing data are adjusted after reflecting the relationship between the datum and TP at each station (**Table 1**). Since the Tokuyama station gives the longest information on sea level change, we demonstrate the detailed data analysis procedure for estimating the future extreme sea level hereinafter with the sea level records from the Tokuyama station. **Table 1** shows the details of the observations at 17 stations including the locations, the available periods, the percent of missing data, the datum and the operating and managing organizations.

### 2.2 Trend and detrending

In the data analysis, finding a trend and removing the trend found is one of most basic and important steps. However, there is neither precise definition of “trend” nor any logical algorithm for detrending it. As a result, there are various ad hoc extrinsic methods available for determining trend and detrending it, such as from the most common straight line best fit based on simple linear trend to a moving average method. Such a simple trend is suit for linear and stationary data, and the moving average method requires a predetermined time scale which is unknown *a priori* for non-stationary processes. In general curve-fitting and filtering methods, data fits to predetermined parametric functions which are subjective often based on assumptions of stationarity and linearity. Sea level changes are non-stationary and non-linear natural processes in which the underlying physical processes and their non-linear interactions affecting sea levels are not completely known.

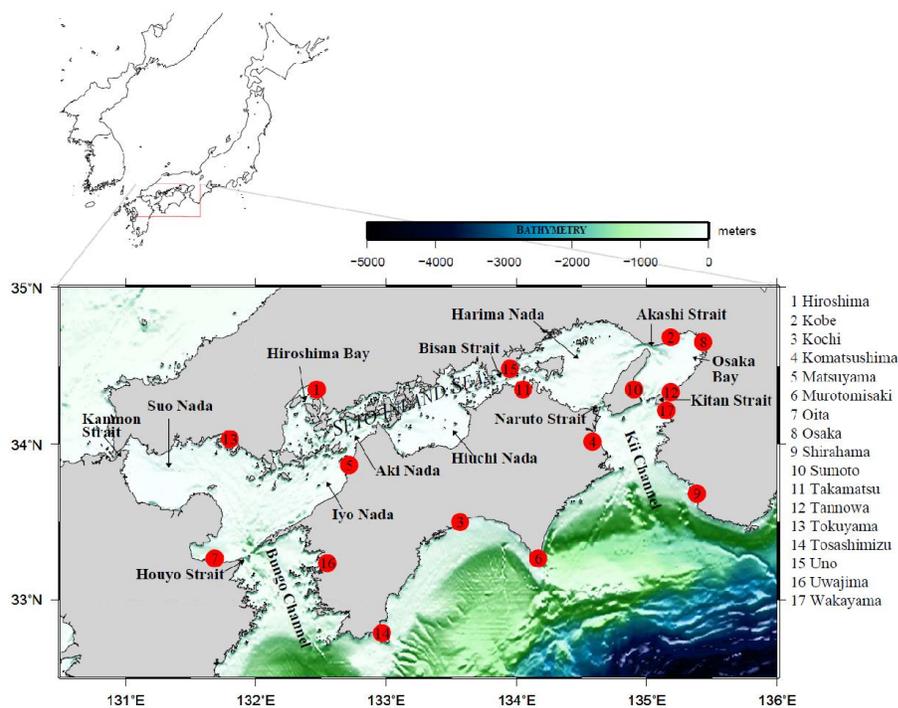


Fig.1 Tidal stations for sea level records in and around the Seto Inland Sea (SIS). Nada in Japanese means basin.

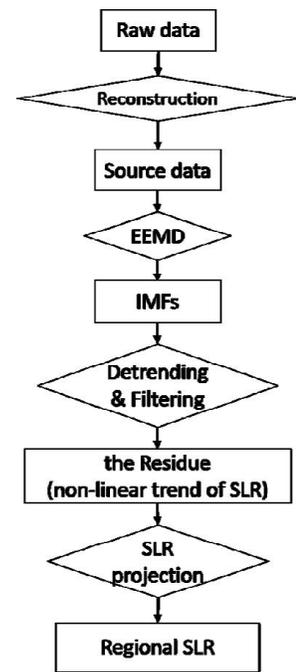


Fig.2 Analysis procedure for regional projection of SLR using EEMD

Based on Wu et al. (2007), we use the following definitions for trend and detrending.

*“The trend is an intrinsically fitted monotonic function or a function in which there can be at most one extremum with a given data span.”*

*“Detrending is the operation of removing the trend. The variability is the residue of the data after the removal of the trend within a given data span.”*

The given data span in the trend definition could be a part or the whole length of the data used.

Based on the definition of trend above, we determined the whole length of dataset used as for the data span. Therefore, the residue is selected as the non-linear trend representing a local property of the data, which is the overall trend of SLR within the whole data span at each station.

### 2.3 Empirical mode decomposition

In contrast to the general curve-fitting and filtering methods, empirical mode

decomposition (EMD) method is empirical, intuitive, direct, and adaptive, without requiring any predetermined parametric functions for determining trend and detrending (Huang et al., 1999; Huang et al., 1998). Therefore, it suits for the purpose of finding out the intrinsic monotonic function for trend and detrending from nonstationary and nonlinear dataset.

The decomposition is based on the simple assumption that any data consists of different simple intrinsic modes of oscillations. This method is also based on the direct extraction of energy associated with various intrinsic time scales. Each of these oscillatory modes is represented by an intrinsic mode function (IMF) while satisfying the following conditions: (1) in the whole data set, the number of extrema and the number of zero-crossings must either be equal or differ by, at most, one; and (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The IMF can have both variable amplitude and frequency as

functions of time, whereas the simple harmonic function has constant amplitude and frequency. IMFs with periods that are too long relative to the data length to be separated by spectral analysis methods can still be identified and decomposed by the EMD.

The EMD decomposes an arbitrary data set  $x(t)$ , in terms of IMFs,  $C_j(t)$ , and a residue,  $R_n(t)$ , through a “sifting process”, where  $j = 1, 2, 3, \dots, n$ . Therefore, the original data  $x(t)$  can be reconstructed by adding up all modes and the residue,  $x(t) = C_1(t) + C_2(t) + C_3(t) + \dots + R_n(t)$ . The  $R_n(t)$  could be a simple constant or a monotonic functions from which no more oscillatory IMFs can be extracted. In the case of sea level records analysis, it is the trend of SLR.

Ensemble empirical mode decomposition (EEMD) is the improved method for obtaining IMFs with more direct physical meaning and greater uniqueness (Wu and Huang, 2009). The EEMD defines the true IMF components as the mean of an ensemble of trials, which consist of the time series plus the white noise of finite amplitude. This method dramatically improves the mod mixing problem due to the subject selection of scale in scale separation. The EEMD method was applied in this study to analyse the sea level records. The EEMD were tested with respect to the optimum number of

ensemble in EEMD analysis. The result showed that ensemble number larger than 20 gives a robust result in terms of the statistical significance of resulting IMFs. Therefore, the number of ensemble was set to 30 for all analyses with the standard deviation of 0.2.

#### 2.4 Statistical significance test

To determine whether a dataset or its components contain useful information, statistical significance tests were performed based on the characteristics of Gaussian white noise with EEMD. The tests determined whether (a) the EEMD is an effective dyadic filter capable of separating white noise into IMFs having mean periods exactly twice the value of the previous one, (b) the IMFs are all normally distributed, and (c) the Fourier spectra of IMF components are identical in shape and cover the same area on a semi-logarithmic period scale. These characteristics were then used to determine the relationship between the product of the mean energy density of an IMF and its corresponding mean period as well as the spread function of the energy density. The characteristics and the resultant relationships were verified with the Monte-Carlo simulation following the method of Wu and Huang (2004), which analyses a large synthetically generated Gaussian white noise dataset.

Table 1. Summary of observational stations and sea level records used for SLR analysis

No.	Station	Location		Data period	Missing (%)	Interval (hr)	Datum (TP, Unit: cm)	Managing organization
		Lat (E)	Long (N)					
1	Hiroshima	34°21'	132°28'	Jan. 1952-	4.10	1	-308.0	JCG
		34.35	132.4667	Dec. 2010				
2	Kobe	34°41'	135°11'	Jan. 1965-	2.30	1	-168.2	JMA
		34.6833	135.1833	Dec. 2009				
3	Kochi	33°30'	133°34'	Jan. 1968-	13.34	1	-95.4	JMA
		33.5	133.5667	Dec. 2009				
4	Komatsushima	34°1'	134°35'	Jan. 1964-	5.54	1	-191	JMA
		34.0167	134.5833	Dec. 2009				
5	Matsuyama	33°52'	132°43'	Jan. 1961-	2.21	1	-214.7	JMA
		33.8667	132.7167	Dec. 2009				

No.	Station	Location		Data period	Missing (%)	Interval (hr)	Datum (TP, Unit: cm)	Managing organization
		Lat (E)	Long (N)					
6	Murotomisaki	33°16'	134°10'	Jan. 1967-	7.24	1	-292.6	JMA
		33.2667	134.1667	Dec. 2009				
7	Oita	33°16'	131°41'	Jan. 1967-	2.03	1	-309.5	JCG
		33.2667	131.6833	Dec. 2010				
8	Osaka	34°39'	135°26'	Jan. 1961-	2.11	1	-353.7	JMA
		34.65	135.4333	Dec. 2009				
9	Shirahama	33°41'	135°23'	Jan. 1968-	1.41	1	-314.2	JMA
		33.6833	135.3833	Dec. 2009				
10	Sumoto	34°21'	134°54'	Jan. 1965-	1.31	1	-184.5	JMA
		34.35	134.9	Dec. 2009				
11	Takamatsu	34°21'	134°3'	Jan. 1965-	1.31	1	-189.8	JMA
		34.35	134.05	Dec. 2009				
12	Tannowa	34°20'	135°11'	Jan. 1967-	3.91	1	-173	JMA
		34.3333	135.1833	Dec. 2009				
13	Tokuyama	34°2'	131°48'	Jan. 1950-	2.04	1	-256.3	JCG
		34.0333	131.8	Dec. 2010				
14	Tosashimizu	32°47'	132°58'	Jan. 1961-	0.2	1	-156.1	JMA
		32.7833	132.9667	Dec. 2009				
15	Uno	34°29'	133°57'	Jan. 1965-	5.69	1	-171.6	JMA
		34.4833	133.95	Dec. 2009				
16	Uwajima	33°14'	132°33'	Jan. 1964-	5.26	1	-207.8	JMA
		33.2333	132.55	Dec. 2009				
17	Wakayama	34°13'	135°9'	Jan. 1967-	2.54	1	-94.3	JMA
		34.2167	135.15	Dec. 2009				

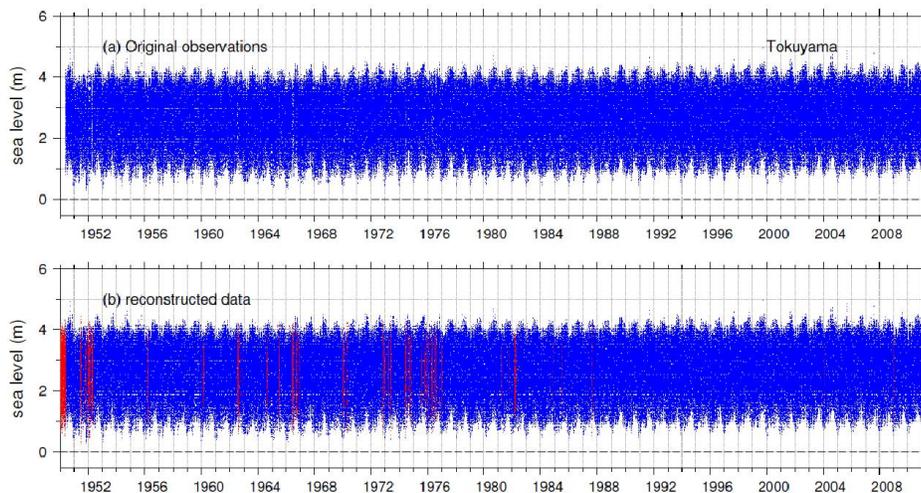
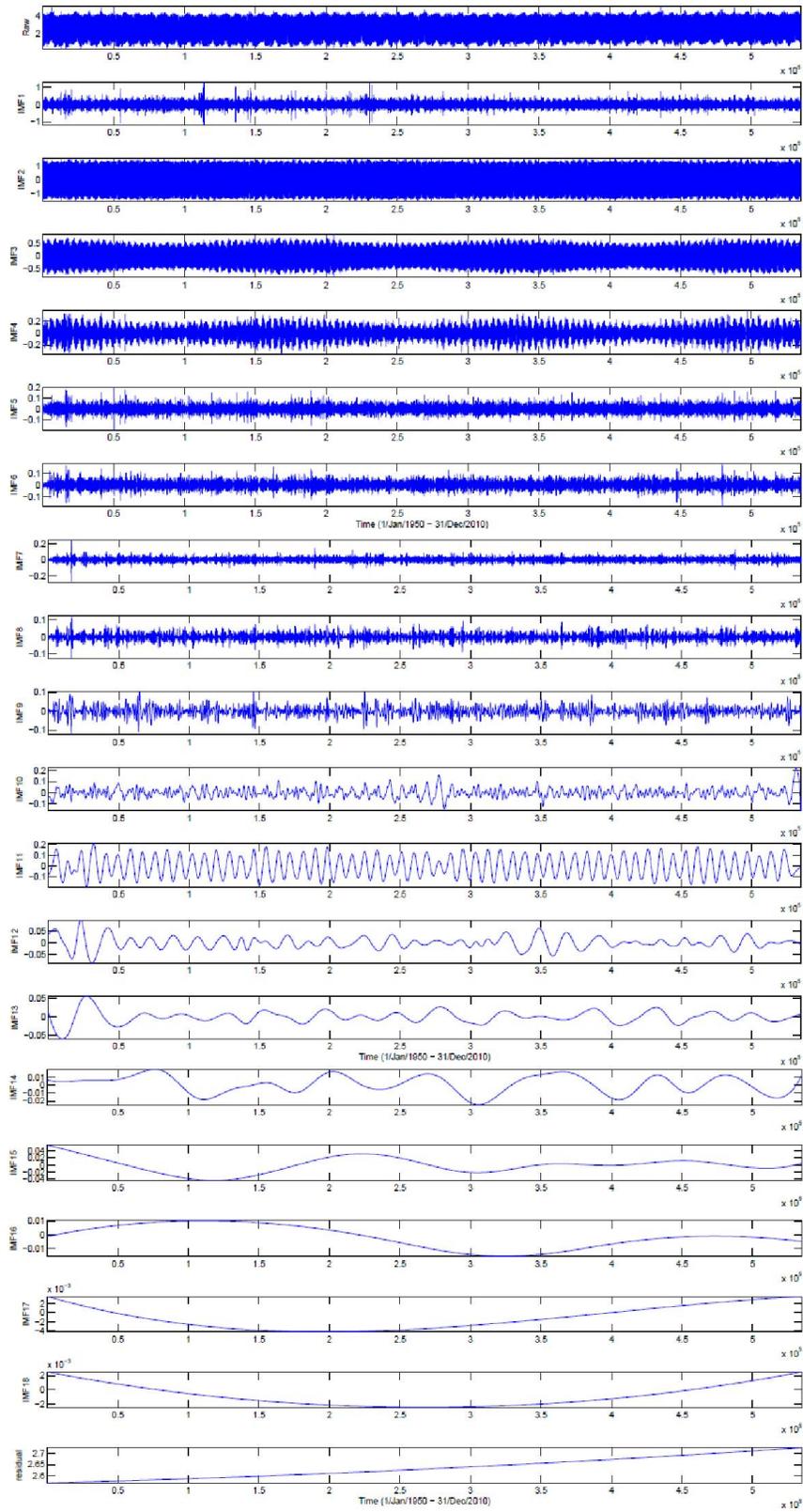


Fig.3 (a) Original observed raw data at Tokuyama and (b) the reconstructed source data after filling in the missing gaps with supplementary predicted data using a high-resolution tide model.



*Fig. 4 The reconstructed source data (Raw), the IMFs 1~18, and the residue at Tokuyama obtained from EEMD*

Because EEMD is the improved method in terms of the physical meaning of IMFs, the results of EEMD of the sea level records in the SIS showed that all IMFs are statistically significant at the 95% and 99% confidence-limit levels. As mentioned, the EEMD with many ensembles improves the statistical significance of IMFs dramatically.

### 2.5 Analysis procedure

**Figure 2** depicts the procedure of data analysis and statistical modelling for estimating the extreme sea level using EEMD and EVA.

First, since the observed records at Tokuyama contain intermittent missing data, a reconstruction of data is carried out by filling in the missing data with supplementary predicted tides generated using NAO99 global tide model (Matsumoto et al., 2000). **Figure 3** illustrates (a) the original raw data and (b) the reconstructed source data with the predicted tides in red.

Second, the reconstructed source data is applied to EEMD with 30 ensembles. The EEMD produces 18 IMFs from high to low frequencies and the residual from the source data (**Fig. 4**). The statistical significant test is, then, performed to ensure the significance levels of all IMFs. The result shows that all IMFs are statistically significant at 99% confidence limit.

Third, after ensuring the significance levels of IMFs, the residual is removed from the EEMD results for detrending the reconstructed source data. The EEMD is used as a tool for detrending and filtering method in this process. In other words, by applying the EEMD, we can detrend the source data and filter out tidal components concurrently and automatically.

Finally, for future projection of SLR, we use the above-mentioned residue from the EEMD results as the non-linear trend of sea level change. In addition to the volume and mass changes of sea water, there are many other factors contributing to sea level change such as river discharge, sediments, and land subsidence (Miller and Douglas, 2004). We interpret that the non-linear trend represents the sea level

change resulting from the non-linear interaction among those factors. To project of future SLR, we use the current non-linear trend of the reconstructed source data. We tried various functions and selected a quadratic polynomial, which fits exactly the non-linear trend of sea level change ( $r=1.0$ ). Then, the polynomial function is extended straightforward to predict the sea level change to 2100 (**Fig. 5**). Therefore, the current acceleration of the sea level rise in the non-linear trend is taken into account in the future prediction.

## 3. RESULTS AND DISCUSSIONS

### 3.1 IMFs from EEMD

IMFs of the sea level records at Tokuyama, decomposed using the EEMD method described above, are shown in **Fig. 4**. The figure depicts that IMF1 is composed of the finest timescales, or highest frequency, and the timescale increases as the index  $j$  of IMF $_j$  increases. Interestingly, the result of statistical significance test showed that all IMFs are statistically significant at the 99% confidence level.

As can be noted, the IMF2 and IMF3 correspond to the composites of semi-diurnal and diurnal tides, respectively. Due to its adaptive nature of EEMD method, it is possible to interpret that the semi-diurnal tides such as  $M_2$ ,  $S_2$ ,  $N_2$ , and  $K_2$  are embedded in the IMF2. Analogous to the case of IMF2, the IMF3 can represent the mixed signal of diurnal tides such as  $K_1$ ,  $O_1$ ,  $P_1$ , and  $S_1$ . IMF11 indicates the clear seasonal cycle due to annual tendency of the context of East Asian monsoon in the sea level. Those three IMF 2, 3, and 11 depict the highest normalized energy density in the signal based on the result of significance test.

The highest frequency IMF1 can be interpreted as a sea level response to weather, termed as weather cycle in *Tebaldi et al.* (2012). In the Pacific Ocean, the El Niño and La Niña episodes have irregular intervals for their occurrence of 3-5 years (in the historical record, this interval varies from 2 to 7 years) (Lee et al., 2012). Since the oscillatory IMFs contain possible physical meanings, the IMF12, IMF13

and IMF14 may correspond to the irregular occurrence intervals of the El Niño and La Niña episodes. IMF7, IMF8 and IMF10 may correspond to the lunar fortnightly tide,  $M_f$ , the lunar monthly tide,  $M_m$ , and the solar semi-annual tide,  $S_{as}$ , based on their mean periods. They are the examples of how the IMFs can be interpreted. However, due to our limited knowledge on physical phenomena causing the sea level responses, it is still challenging and needs various and thorough case studies to find out the physical meanings for each IMF depending on one's objectives.

Upon the purpose of this study to estimate the regional SLR, we only use the residue as the current non-linear trend of SLR in the next step.

In addition, we can reconstruct the storm surge levels by combining all non-tidal IMFs after only removing the IMF2 and IMF3 and the residual, corresponding to composites of semi-diurnal and diurnal tides and the non-linear trend, respectively, as indicated above, following the definition of storm surge. This is just an example to show how to use the EEMD results for one's purpose.

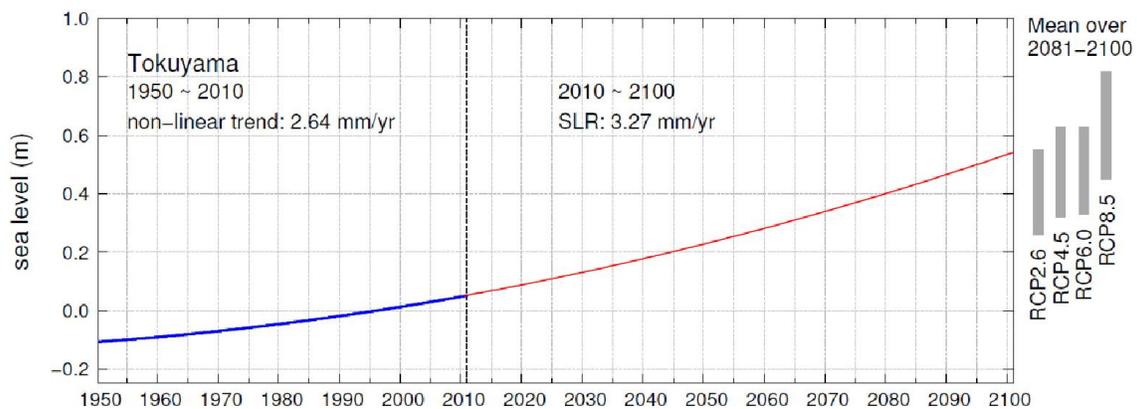


Fig. 5 The non-linear SLR trend from 1950 to 2010 (blue) and its regional projection by 2100 (red) at Tokuyama, relative to 1986-2005. The global mean sea level rise from the IPCC AR5 are shown together as shaded bands for reference.

Table 3. SLR trend of the available periods, the current period (1993~2010), and SLR projections in 2050 and 2100 at all stations in the Seto Inland Sea.

N o	Station	Trend (mm/yr)		Sea level rise (m)	
		Available period	1993~	2050	2100
1	Hiroshima	+4.44	+5.18	+0.20	+0.46
2	Kobe	+8.23	+17.71	+1.46	+4.72
3	Kochi	+0.78	+6.17	+0.74	+2.61
4	Komatsushima	+1.55	+1.27	+0.02	+0.00
5	Matsuyama	+0.77	+0.22	-0.03	-0.15
6	Murotomisaki	+5.11	+7.01	+0.43	+1.25
7	Oita	+3.30	+2.47	+0.01	-0.13
8	Osaka	+10.25	+3.82	-0.35	-1.72
9	Shirahama	-0.93	+0.06	+0.11	+0.44
1	Sumoto	+2.48	+2.69	+0.12	+0.28

N	Station	Trend (mm/yr)		Sea level rise (m)	
		Available period	1993~	2050	2100
0					
1	Takamatsu	+1.87	+1.21	-0.01	-0.15
1	Tannowa	+1.54	+1.52	+0.05	+0.10
2	Tokuyama	+2.64	+3.58	+0.18	+0.49
3	Tosashimizu	+1.03	+2.02	+0.15	+0.46
4	Uno	+5.00	+3.84	+0.04	-0.13
5	Uwajima	+0.68	+1.05	+0.07	+0.21
6	Wakayama	-0.76	-0.48	+0.01	+0.07
7					

### 3.2 Regional SLR projection

As a result of EEMD method, the residue is obtained together with IMFs. As described earlier, we interpret the residue as the non-linear trend of sea level records. The annual rates of sea level changes at Tokuyama are 2.64 mm/yr for 1950 ~ 2010 and 3.58 mm/yr for 1993 ~ 2010 which is slightly larger than the altimetry-based global average SLR rate of  $3.3 \pm 0.4$  mm/yr from 1993-2007 (Cazenave and Llovel, 2009). To predict the future SLR to 2100, the non-linear trend is fitted to a quadratic polynomial ( $r=1.0$ ). Then, the polynomial is extended to the year of 2100 for SLR projection taking into account the current acceleration trend of SLR. The resulting SLR from 2010 to December 2100 is 0.49 m with average annual rate of 3.27 mm/yr (**Fig. 5**). Sea level records from all other 16 stations in the SIS were applied to the same analysis procedure and the results are summarized in **Table 2**.

### 4. CONCLUSIONS

We have introduced a novel approach to project regional SLR with an adaptive data analysis method, EEMD, using a long-term

observed sea level records at Tokuyama in the SIS, Japan.

The EEMD method successfully decomposes the sea level records into IMFs and the residue. The non-linear SLR trend could also be identified and obtained from the residual. The annual mean rates of SLR at Tokuyama obtained are 2.64 mm/yr from 1950 to March 2010 and 3.58 mm/yr from April 1993 to March 2010, which is slightly larger than the altimetry-based rate of global average SLR of  $3.3 \pm 0.4$  mm/yr over 1993-2007. The SLR projection in 2050 and in 2100 obtained are 0.18 m and 0.49 m, respectively.

In many reported adaptation strategies to future SLR, for example, in Bangladesh which is one of the most vulnerable countries to SLR and storm surge, the SLR scenarios are based on the average of global projection from GCMs with high uncertainty in ice sheets contribution to SLR. Moreover, the local effects such as uplifting and subsidence are not considered in the SLR scenarios. In adaption strategies to climate change, however, the SLR scenarios due to global warming and local effects, and its

estimation are not trivial and have to be estimated physically and statistically sound. In coastal engineering point of view, the information from the SLR is a critical factor in coastal defense for future climate change. Therefore, we hope the introduced novel method using EEMD would help improve the procedures of assessments and adaptations to climate change and in coastal defense.

In addition, coastal hazards due to flood events are almost invariably associated with extreme sea levels by tropical cyclone-induced storm surges. Therefore, the impacts of global warming on coastal flood risk depend heavily on the future trend in extreme surges. In the case of Bangladesh, Lee (2013) showed how to estimate the extreme sea levels for regional SLR scenarios by combining the regional projection of long-term SLR and the short-term extreme

storm surges.

With respect to the SLR projection, a semi-empirical approach was suggested to project SLR by connecting global SLR to global mean surface temperature (Rahmstorf, 2007; Tebaldi et al., 2012; Vermeer and Rahmstorf, 2009). They showed that the semi-empirical formula hold to good approximation for temperature and sea level changes during the 20th century. In a future work, we improve the SLR projection by comparing and applying the semi-empirical formula rather than simply expanding a polynomial to future.

## 5. ACKNOWLEDGEMENTS

This study is supported by the Grant-in-Aid for Young Scientists (B) and the Grant-in-Aid for Challenging Exploratory Research of MEXT.

## 6. REFERENCES

1. Ali, A. (1996). Vulnerability of Bangladesh to climate change and sea level rise through tropical cyclones and storm surges. *Water, Air, & Soil Pollution*, **92**(1), 171-179.
2. Ali, A. (1999). Climate change impacts and adaptation assessment in Bangladesh. *Climate Research*, **12**(2-3), 109-116.
3. Cazenave, A., and Llovel, W. (2009). Contemporary Sea Level Rise. *Annual Review of Marine Science*, **2**(1), 145-173.
4. Huang, N. E., Shen, Z., and Long, S. R. (1999). A new view of nonlinear water waves: The Hilbert spectrum. *Annu. Rev. Fluid Mech.*, **31**(1), 417-457.
5. Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., Yen, N. C., Tung, C. C., and Liu, H. H. (1998). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proc. R. Soc. London.*, **454**(1971), 903-995.
6. IPCC (2007). Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor and H. L. Miller, Cambridge University Press Cambridge, United Kingdom and New York, NY, USA.
7. Karim, M. F., and Mimura, N. (2008). Impacts of climate change and sea-level rise on cyclonic storm surge floods in Bangladesh. *Global Environ. Change*, **18**(3), 490-500.
8. Lee, H. S. (2013). Estimation of extreme sea levels along the Bangladesh coast due to storm surge and sea level rise using EEMD and EVA. *Journal of Geophysical Research: Oceans*, n/a-n/a.
9. Lee, H. S., Yamashita, T., and Mishima, T. (2012). Multi-decadal variations of ENSO, the Pacific Decadal Oscillation and tropical cyclones in the western North Pacific. *Progress In Oceanography*, **105**(0), 67-80.
10. Lee, H. S., Yamashita, T., Komaguchi, T., and Mishita, T. (2010). Storm surge in Seto Inland Sea with Consideration of the Impacts of Wave Breaking on Surface Currents. *Proc. of the 32<sup>nd</sup>*

*International Conference on Coastal Engineering*, **32**, current 17.

11. Matsumoto, K., Takanezawa, T., and Ooe, M. (2000). Ocean Tide Models Developed by Assimilating TOPEX/POSEIDON Altimeter Data into Hydrodynamical Model: A Global Model and a Regional Model Around Japan. *Journal of Oceanography*, **56**, 567-581.
12. Miller, L., and Douglas, B. C. (2004). Mass and volume contributions to twentieth-century global sea level rise. *Nature*, **428**(6981), 406-409.
13. Rahman, A. e. a. (2009). Policy study on the probable impacts of climate change on poverty and economic growth and the options of coping with adverse effect of climate change in Bangladesh, *Rep.*, 117 pp, General Economics Division, Planning Commission, Government of the People's Republic of Bangladesh & UNDP Bangladesh, Dhaka, Bangladesh.
14. Rahmstorf, S. (2007). A Semi-Empirical Approach to Projecting Future Sea-Level Rise. *Science*, **315**(5810), 368-370.
15. Rahmstorf, S. (2010). A new view on sea level rise. *Nature Reports Climate Change*(1004), 44-45.
16. Ruane, A. C., et al. (2013). Multi-factor impact analysis of agricultural production in Bangladesh with climate change. *Global Environ. Change*, **23**(1), 338-350.
17. Sarwar, M. G. M. (2005). *Impacts of Sea Level Rise on the Coastal Zone of Bangladesh*. M.S. thesis, Lund University International Masters Programme in Environmental Science (LUMES), Lund University, Lund, Sweden.
18. Tebaldi, C., Strauss, B. H., and Zervas, C. E. (2012). Modelling sea level rise impacts on storm surges along US coasts. *Environmental Research Letters*, **7**(1), 014032.
19. Tsuge, T., and Washida, T. (2003). Economic valuation of the Seto Inland Sea by using an Internet CV survey. *Marine Pollution Bulletin*, **47**(1-6), 230-236.
20. Vermeer, M., and Rahmstorf, S. (2009). Global sea level linked to global temperature. *Proceedings of the National Academy of Sciences*, **106**(51), 21527-21532.
21. Willis, J. K., and Church, J. A. (2012). Regional Sea-Level Projection. *Science*, **336**(6081), 550-551.
22. Wu, Z., and Huang, N. E. (2004). A study of the characteristics of white noise using the empirical mode decomposition method. *Proc. R. Soc. London.*, **460**(2046), 1597-1611.
23. Wu, Z., and Huang, N. E. (2009). Ensemble empirical mode decomposition: A noise-assisted data analysis method. *Advances in Adaptive Data Analysis*, **1**(1), 1-41.
24. Wu, Z., Huang, N. E., Long, S. R., and Peng, C.-K. (2007). On the trend, detrending, and variability of nonlinear and nonstationary time series. *Proceedings of the National Academy of Sciences*, **104**(38), 14889-14894.
25. Yamamoto, T. (2003). The Seto Inland Sea--eutrophic or oligotrophic? *Marine Pollution Bulletin*, **47**(1-6), 37-42.
26. Yanagi, T., Takeoka, H., and Tsukamoto, H. (1982). Tidal energy balance in the Seto Inland Sea. *Journal of Oceanography*, **38**(5), 293-299.

---

Người phản biện: **TS. Trần Thanh Tùng**

BBT nhận bài: 25/10/2013  
Phản biện xong: 7/11/2013