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Stochastic Analysis of Typhoon-Induced Storm Surge in the Coastal Area of the Korean Peninsula: Inference from a Nonstationary, Bayesian, Poisson, Generalized Pareto Distribution

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ABSTRACT

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Climate-related disasters in East Asia have been recently increasing due to enhanced climate variability and climate change. Moreover, the frequency and intensity of typhoons and associated disasters in the East Asia region have been increasing steadily over the past few decades. In fact, the Korean Peninsula is considered among the most disaster-prone areas, largely due to the incidence of typhoons. In particular, it is expected that the potential risk of flooding in coastal areas would be greater in the presence of a simultaneous storm surge and heavy rainfall. In this context, understanding the mechanism of interaction between the two factors and estimating the risk associated with their concurrent occurrence are of particular interest because of their impact on in low-lying areas. In this study, we developed a Poisson-Generalized Pareto Distribution (Poisson-GPD)-based nonstationary storm surge frequency model to combine the occurrence of an exceedance of a high threshold and a peak over threshold (POT) within a Bayesian framework. Here, the GPD is employed to describe the maximum storm surge distribution for each typhoon with a storm surge exceeding a certain level using a time-varying scale and shape parameter. On the other hand, the number of typhoons in each year exceeding the storm surge threshold follows a Poisson distribution with a time-varying lambda parameter.

ADDITIONAL INDEX WORDS: *Typhoon, Storm surge, Bayesian, Poisson-GPD, Risk analysis.*

INTRODUCTION

The rise in sea level due to climate change and the increase in the intensity and frequency of typhoons is exacerbating flood damage due to storm surges in coastal areas of South Korea. In order to minimize such damages, it is necessary to develop a reliable model for evaluating the risks associated with coastal flooding. In the past three decades, an increase in sea level has been observed due to enhanced climate variability and climate change (Morey *et al*., 2006; Lee *et al*., 2010). The purpose of this study is to develop an extreme sea level frequency analysis technique considering typhoon occurrence (Church *et al*., 2006).

Understanding the severity of typhoon-induced storm surges helps in planning for potential disasters and mitigating their effects. More generally, a storm surge is a phenomenon mainly due to changes in wind and air pressure caused by various factors such as typhoons and developed extratropical cyclones. A storm surge generally occurs when the central pressure of a typhoon is exceptionally low, leading to an excessive and temporary sea level rise. This is called the inverse barometer effect. Based on the historical record of the occurrence of extreme low pressure events (or typhoons), there have been many studies linking low pressure systems with their associated damages by introducing prediction models (Flather, 1976; Lee, 2008).

The Korean peninsula has suffered from serious floods and storm surges associated with heavy rainfall accompanied by typhoons. In addition, there is a continuous process of urbanization, especially along the coastline, which results in a high density of people and properties in coastal cities (Webster *et al*., 2005; Guo *et al*., 2009). With the aforementioned factors in mind, we developed a Poisson-Generalized Pareto Distribution (Poisson-GPD)-based sea level frequency method that allows us to simultaneously explore changes in the amount and exceedance probability of extreme sea level events caused by typhoons. This study utilized a Bayesian approach to better estimate both parameters and their uncertainties (Kwon *et al*., 2008; Lima and Lall, 2010).

Due to recent weather patterns, the current statistical characteristics of extreme events are markedly different from the past characteristics. In addition, in the data analysis of extreme events, it is becoming increasingly difficult to evaluate changes in frequency and intensity of extreme events due to sampling errors related to probability distribution selection and outliers. In this regard, a Bayesian approach has been widely used to better quantify the uncertainties associated with either the relevant

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parameters or the modeling process (Ouarda and Adlouni, 2008; Sun *et al*., 2015).

DATA

Every year on average, the Korean coast is directly and indirectly affected by three to four typhoons (Table 1). The coastal disasters caused by strong winds, high waves, heavy rainfall, and typhoon-induced storm surges have led to significant damage. Moreover, increasing urbanization and population densities in coastal areas is likely to further intensify future damages.

Typhoons have different damage patterns depending on the path, wind speed and direction, and evolution of the storm. It is particularly necessary to properly assess the scale of the abnormal sea level rise events for coastal protection facilities, ports, and coastal structures. A main goal of marine observations is to periodically measure and analyze phenomena such as sea level changes and storm surges and to utilize this analysis in the design of coastal structures.

The Korea Hydrographic and Oceanographic Agency (KHOA) operates the Korea Ocean Observing Network (KOON) that consists of sea level stations, ocean stations, ocean buoys, surface current stations, and ocean research stations. KOON provides real time ocean information with improved data quality in order to meet the needs of oceanic industries, the military, and the general public (http://www.khoa.go.kr).

Table 1. *The yearly number of typhoons, with the number affecting the Koran Peninsula in parentheses.*

Year	Typhoon Number	Year	Typhoon Number
1987	23(3)	2002	26(4)
1988	31(0)	2003	21(4)
1989	32(2)	2004	29(5)
1990	29(4)	2005	23(1)
1991	29(5)	2006	23(3)
1992	31(2)	2007	24(3)
1993	28(4)	2008	22(1)
1994	36(5)	2009	22(0)
1995	23(3)	2010	14(3)
1996	26(2)	2011	21(3)
1997	28(4)	2012	25(5)
1998	16(2)	2013	31(3)
1999	22(5)	2014	23(4)
2000	23(5)	2015	27(4)
2001	26(1)	2016	26(2)

These stations collect, analyze, and release various data related to sea levels, water temperatures, waves, ocean currents, and marine weather. This information has been used for the protection of the coastal environment and for maritime safety management. KOON is a group of instruments and infrastructures designed to effectively manage and monitor oceanic conditions within Korea's sovereign marine areas. The collection and analysis of ocean data have enhanced the understanding of Korea's jurisdictional sea area and have improved the national capability for utilization, development, and preservation of marine structures and has aided disaster mitigation efforts. The sea level data are collected at major harbors and stations located near the islands (Figure 1). Among the many sea level stations of KOON, we used 20 stations that have more than 30 years of data for the frequency analysis.

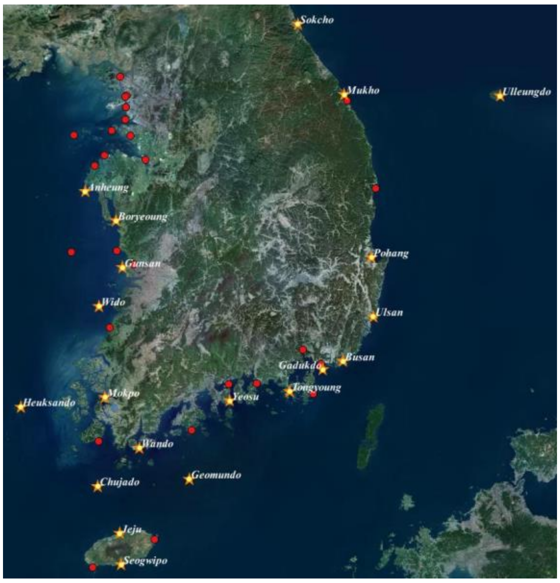

Figure 1. Locations of sea level stations.

METHOD

This study was conducted in two stages. For the first step, a trend test was conducted to evaluate the tendency of sea level rise during storm surges. Secondly, the sea level frequency analysis using the Poisson-GPD model was performed within a Bayesian framework.

Mann-Kendall Trend Test for Sea Level

The variability of the sea level data series can be quantitatively analyzed through various statistical techniques. Among these approaches, we used the Mann-Kendall test (M-K test) (Mann, 1945; Kendall, 1975), which is widely used to determine the trend of a hydrologic time series. The procedure of the M-K test is summarized as follows.

The M-K test is performed by comparing the time series of $S_t(t = 1,2,\cdots N)$ and $S_{s'}(t = 1,2,\cdots N-1)$. The sign values are calculated by equations (1a), (1b), and (1c), where z(k) represents $S_t - S_{t'}$.

$$\text{z(k)} = 1 \text{ if } S_t > S_{t'} \quad (1a)$$

$$\text{z(k)} = 0 \text{ if } S_t = S_{t'} \quad (1b)$$

$$\text{z(k)} = -1 \text{ if } S_t < S_{t'} \quad (1c)$$

Here, the number k is $N(N-1)/2$, and the values of S_t and, $S_{t'}$ are calculated. The M-K test statistic values Q can be expressed as follows (Equation (2)).

$$Q = \sum_{K=1}^{N(N-1)/2} z(k) \quad (2)$$

Q is used to calculated the test statistics u and the variance $V(Q)$ as in equations (3a) and (3b).

$$u = \frac{Q+m}{\sqrt{V(Q)}} \tag{3a}$$

$$V(Q) = \frac{1}{18}[N(N-1)(2N+5)] \tag{3b}$$

Equation (3) has a value of 1 for $Q < 0$ and a value of -1 for $Q > 0$. The M-K test is applied under the null hypothesis that there is no tendency using the calculated test statistics u, and the null hypothesis can be rejected for the region of $|u| > z_{1-a/2}$. Here, z follows the standard normal distribution, and the M-K test is performed at a 10% significance level (Pingale *et al*., 2016).

Poisson-GPD Model

The sea level frequency analysis results plays a crucial role in designing marine structures because the frequency analysis results are typically required for the design. In addition, frequency of occurrence of the extreme sea level induced by the typhoons has become a major issue in marine engineering.

It is advantageous to perform reliable frequency analysis using all data exceeding the threshold when analyzing extreme data corresponding to the right tail of the time series marginal distribution (Divison and Smith, 1990).

In this study, the storm surges occurring during typhoons were analyzed, and sea level frequency analysis was performed. Assuming that the extracted extreme values are independent identically distributed (IID) for the random variable X, if a value exceeding the threshold u is defined as $y = X - u$, then the conditional probability distribution is given as

$$P\{X > u + y | X > u\} = \frac{1-F(u+y)}{1-F(u)} \tag{4}$$

Equation (4) can be summarized by converting it to the form of the GPD function. Equations (5a) and (5b) are finally organized as equation (6).

$$1 - F(u+y) = \exp(-[1 + \xi\frac{(u+y-\mu)}{\sigma}]^{-1/\xi}) \tag{5a}$$

$$1 - F(u) = \exp(-[1 + \xi\frac{(u-\mu)}{\sigma}]^{-1/\xi}) \tag{5b}$$

$$P\{X > u + y | X > u\} = [1 + \frac{\xi \cdot y}{\tilde{\sigma}}]^{-1/\xi} \tag{6}$$

Here, $\tilde{\sigma}$ represents $\sigma + \xi(u - \mu)$, σ is a scale parameter, and ξ is a shape parameter defined as an extreme value index or a tail index.

The variable ξ characterizes the shape of the tail, with $\xi > 0$ representing a heavy tail and $\xi < 0$ having a short tail. u is a parameter that governs the threshold and is set as the minimum sea level of a storm surge in this study. Here, $P\{X > u\} = \zeta_u$ can be expressed as follows.

$$P\{X > u + y | X > u\} = GPD(x - u|\sigma, \xi) = [1 + \frac{\xi(x-u)}{\tilde{\sigma}}]^{-1/\xi} \tag{7a}$$

$$P\{X > x\} = \zeta_u\left[1 + \xi\frac{(x_m - u)}{\tilde{\sigma}}\right]^{-\frac{1}{\xi}} = \frac{1}{m} \tag{7a}$$

This peak over threshold (POT) analysis is specified by the Poisson-GPD method (Madsen *et al*., 1997; Clarke *et al*., 2009).

$$x_m = u + \frac{\sigma}{\xi}[(m\zeta_u{}^{\xi}) - 1] \tag{8}$$

The specific method of the Poisson-GPD method is based on the Poisson distribution with an average of mλ times exceeding the threshold when observations of IID are observed for m years, and the excess value follows the GPD distribution.

The Poisson distribution can be employed to consider typhoons in a more quantitative manner. Intuitively, ζ_u in equation (8) can be assumed to follow the Poisson distribution. The probability distribution function (PDF) of the Poisson distribution is formulated as equation (9), which expresses how many times a specific event occurs during a given unit of time. λ is the expected value of the typhoon events for each year. In this study, the number of occurrences of typhoon events exceeding the threshold was analyzed in relation to the GPD.

$$P(X = x) = \frac{e^{-\lambda}\lambda^x}{x!} \tag{9}$$

Bayesian Inference

Various studies on frequency analysis have adopted the Bayesian inference framework to better describe the uncertainty associated with model parameters (Reis and Stedinger, 2005; Haddad and Rahman, 2012). Bayesian theory specifies that the conditional probability distribution of the parameter θ and random variable X is inferred from the product of the prior distribution and likelihood. In other words, the posterior distribution can quantitatively interpret uncertainty by continuously updating the likelihood and posterior distribution in proportion to the product of the prior distribution and likelihood.

The Poisson-GPD method is described in equations (10a), (10b), and (10c), with these defined parameters representing prior distributions.

$$X_{t,s} \sim GPD(u, \sigma_s, \xi_s) \tag{10a}$$

$$\sigma_s \sim G(k_\sigma, \tau_\sigma) \tag{10a}$$

$$\xi_s \sim exp(\mu_\xi) \tag{10a}$$

The posterior distribution for the parameter estimation through the prior distribution is defined by the Bayesian theorem in equation (11).

$$p(\theta|X) = \frac{P(X|\theta)p(\theta)}{p(X)} \propto p(X|\theta) \cdot p(\theta) \tag{11}$$

Where X is the POT sea level data during a storm surge and θ is a set of parameters. In summary, p(X) is the marginal distribution and p(X|θ) is the likelihood of occurrence. The number of events n that exceed the threshold follows the Poisson distribution with a mean mλ.

Assuming that the extra $z_1 - u, \cdots z_n - u$ that exceeds the threshold follows the GPD, the likelihood is given by equation (12).

$$L(\lambda, \sigma, \zeta) = e^{-m\lambda}\frac{(m\lambda)^n}{n!}\prod_{i=1}^{n}[\frac{1}{\sigma}(1 + \frac{\xi(x_i - u)}{\sigma})^{-\frac{1}{\xi}-1}] \tag{12}$$

In Bayesian theory, the prior probability of the parameter is combined with the information obtained from the data to identify the posterior distribution of the parameter and use the posterior to infer the parameter. In other words, given the prior distributions that are independent of one another, the posterior distribution is given by equation (13).

$$p(\lambda, \sigma, \xi|\text{data}) \propto p(\lambda)p(\sigma)p(\xi)L(\lambda, \sigma, \xi) \tag{13}$$

RESULTS and Discussion

Sea Level Trend Analysis

From 1987 to 2016, there were 92 typhoons that affected the Korean Peninsula. The maximum value of the sea level data during each typhoon period was extracted and the M-K trend test was performed. Of the 20 stations, 19 stations except Gunsan station showed the increases of the maximum sea level during the typhoon season. As shown in Figure 2, typically, Boryeoung and Mokpo stations have a clear tendency to increase the maximum sea level during the typhoon season. Table 2 shows M-K test results for each station.

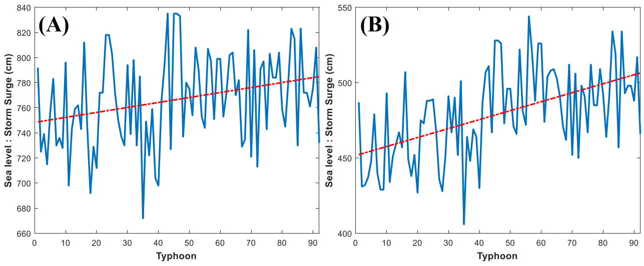

Figure 2. M-K tendency test results at Boryeoung (A) and Mokpo (B)

Table 2. *The result of statistical analysis and trend of storm surge data*

Method	MK		Method	MK	
Station	Trend	Z-value	Station	Trend	Z-value
Anheung	**O**	**2.037**	**Mukho**	**O**	**4.988**
Boryeoung	**O**	**1.902**	**Pohang**	**O**	**3.646**
Busan	**O**	**2.192**	**Seogwipo**	**O**	**1.602**
Chujado	**O**	**1.649**	**Sokcho**	**O**	**3.649**
Heuksando	**O**	**4.064**	**Tongyoung**	**O**	**3.315**
Gadukdo	**O**	**2.590**	**Ulleungdo**	**O**	**2.516**
Geomundo	**O**	**3.261**	**Ulsan**	**O**	**3.771**
Gunsan	X	2.837	**Wando**	**O**	**3.063**
Jeju	**O**	**4.661**	**Wido**	**O**	**2.691**
Mokpo	**O**	**2.337**	**Yeosu**	**O**	**2.890**

Poisson-GPD Analysis

In the case that a tendency exists, as verified by the M-K test, it is likely that an increase in design sea level is necessary to account for an increasing frequency of storm surges. To better estimate the design sea level, this study applied the Poisson-GPD model to the sea level stations where there was a statistically significant increasing tendency. In addition, the frequency analysis results were compared using a general extreme value (GEV) distribution, which is widely used for extreme value analysis.

In the POT analysis, the determination of the threshold plays a crucial role. In this study, the minimum value of the storm surge caused by typhoons was assumed to be a threshold, and the Poisson-GPD was then applied for the events exceeding the threshold. The Bayesian MCMC (Markov chain Monte Carlo) was used to estimate posterior distributions for a set of model parameters. Figure 3 shows the comparison of the design sea level corresponding to the return periods using the posterior distributions derived from the Bayesian MCMC.

As the return period increases, the Poisson-GPD frequency analysis results are relatively larger than those found with the GEV distribution. Although the GEV distribution models are widely used in the design of offshore structures, they do not take into account the nonstationarity associated with the increase in the frequency of typhoons. From this perspective, the estimated design values obtained through the GEV distribution are likely to underestimate the storm surge (Mclnnes *et al*., 2003; Huang *et al*., 2008; Mclnnes *et al*., 2009).

The Bayesian Poisson-GPD model appears to have a favorable advantage in terms of evaluating low-lying inundation and coastal storm surges in regions with an increasing trend of extreme sea level (Figure 3 and Table 3).

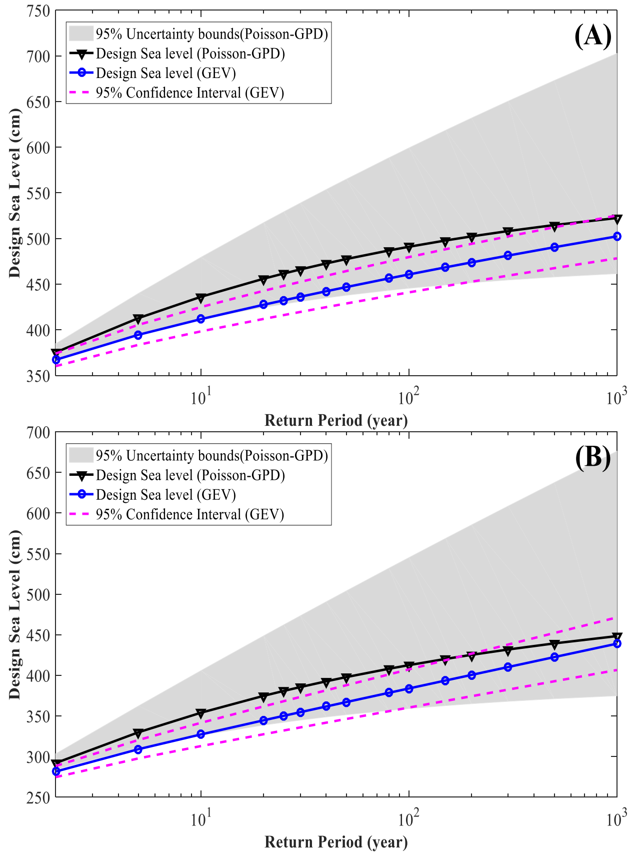

Figure 3. Design sea level and uncertainty estimation results at Heuksando (A) and Tongyoung (B).

Table 3. *Design values and their credible intervals estimated from Poisson-GPD frequency analysis.*

Station Name	Sea Levels (cm)	Return Period (Year)				
		30	50	100	300	500
Gadukdo	5%	234.3	235.9	237.3	238.5	238.9
	mean	255.8	258.9	261.8	264.6	265.4
	95%	290.8	297.8	305.4	314.0	317.0
Pohang	5%	84.0	85.1	86.0	86.8	86.9
	mean	108.1	110.6	112.9	115.1	115.6
	95%	148.8	155.3	162.1	169.3	171.7
Sokcho	5%	77.5	77.9	78.2	78.4	78.5
	mean	102.1	103.9	105.5	106.9	107.3
	95%	149.7	155.3	161.1	167.2	169.1

CONCLUSIONS

Due to climate change, the frequency and scale of natural disasters are increasing worldwide. Global warming is expected to significantly increase temperatures and result in rising sea levels due to the thermal expansion of the oceans and melting glaciers. Particularly for coastal areas, the effects of climate change are expected to be massive. A storm surge is a phenomenon in which the water level at the coast rises sharply to higher than the forecast sea level due to the sudden pressure drop associated with low pressure systems and typhoons. In this study, we developed a Poisson-GPD frequency analysis technique based on a Bayesian framework that can simultaneously consider the frequency and magnitude of storm surges occurring in the Korean Peninsula using a threshold.

This study explored changes in the frequency and magnitude of the typhoon induced storm surge for the gauging stations where the typhoon is considered to be a dominant driver for the storm surge considering the path of typhoons. We compared the difference of design sea levels for the three representative stations under nonstationary assumption. It was found that an increase in the occurrence of storm surges was clearly seen along the paths of typhoons. Most stations listed in Table 1 showed a similar pattern in terms of changes in design values to the stations presented in Table 3. The sea level frequency analysis results confirmed that the use of GEV distribution resulted in underestimation of the design sea level compared to the Poisson-GPD model. Therefore, the use of Poisson-GPD model in the design sea level estimation in coastal areas could be an alternative to better characterize the changes in design sea levels.

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