 

# Bayesian GLS for Regionalization of Flood Characteristics in Korea

Dae Il Jeong[1], Jery R. Stedinger[2], Young-Oh Kim[3], and Jang Hyun Sung[4]

[1] Post-doctoral Fellow, School of Civil and Environmental Engineering, Cornell University, Hollister Hall, Ithaca, NY 14853-3501, PH 607-255-9790, email: dj64@cornell.edu
[2] Professor, School of Civil and Environmental Engineering, Cornell University, Hollister Hall, Ithaca, NY 14853-3501, PH 607-255-2351, email: jrs5@cornell.edu
[3] Associate Professor, School of Civil, Urban and Geosystem Engineering, Seoul National University, Seoul 151-742, Korea, PH +82-2-880-8916, email: yokim05@snu.ac.kr
[4] Graduate Student, School of Civil, Urban and Geosystem Engineering, Seoul National University, Seoul 151-742, Korea, PH +82-2-880-8354, email: kon26@snu.ac.kr

***Abstract***
For ungauged and gauged sites in Korea, the estimation of flood quantiles is a difficult but important problem. The problem is particularly difficult because almost all flood records are short (< 35 years). The index flood method is commonly used because of the short record lengths, but its performance is compromised by the great heterogeneity among Korean basins. Therefore, a regional flood frequency analysis that addresses differences in the coefficients of variation and skewness using physiographic characteristics of the basin is an attractive approach for constructing the best possible quantile estimators at gauged sites, as well as providing estimates of flood characteristics at ungauged locations.

This study presents a Bayesian Generalized Least Square (B-GLS) regression analysis of regional flood frequency data from Korea. The GLS regression framework reflects both the precision of available at-site estimators of flood characteristics and the accuracy of regional models of those statistics. As a result it provides more accurate estimators of model parameters than does ordinary and weighted least square regression analyses, and a nearly unbiased estimator of the model error variance and the precision of estimated parameters. Here B-GLS analyses relate descriptions of scale (the L-CV) and of shape (the L-CS) of the distribution of annual floods to physiographic watershed characteristics, which could include basin index, drainage area, and main channel slope.

***Introduction***
Floods are a continuing problem in Korea, both in terms of reoccurring flash floods that cause local floods effecting small communities, and the potential for large catastrophic floods that would impact densely-populated urban areas which, because of limited space, are often crowed in flood-prone alluvial plains and valley bottoms (MOCT, 2001). Rainfall with very high intensity (> 80 mm/day) is common during the 3-month flood season (July ~ September) when approximately one third of the total annual precipitation (1283 mm) occurs. Such heavy rainfall is transformed to severe floods by the physiographical characteristics of the small and mountainous Korean peninsula.

Flood data are essential for studies addressing flood risk reduction; but, unfortunately, flood record lengths are generally very short in Korea. Only 31 gauging stations are available whose records are longer than 10 years, and their average record length is just 22 years. Because of this data limitation, most Korean flood studies have employed flood data generated with rainfall-runoff models based upon more extensive rainfall data. Rainfall records in Korea are generally longer than 30 years. An alternative is to use regional flood frequency analysis that "substitutes space for time" (National Research Council, 1988). A simple index flood method (Hosking and Wallis, 1997) that allows only variation among station means within a region may not be appropriate because of the potential heterogeneity in the second and higher moments due to the wide variation in basin characteristics. Methods that allow for variation in a shape parameter are often better than simple index flood methods (Stedinger and Lu, 1995), though index flood methods can be improved by regression of normalized quantiles on physiographic basin characteristics or by weighting at-site and regional estimates of the CV (Fill and Stedinger, 1998).

Figure 1 shows the sample L-CV (L-moment Coefficient of Variation) and L-CS (L-moment Coefficient of Skewness) of annual maximum flood data collected from 31 gauging stations in Korea. The data show great variability due to sampling errors as well as the natural site-to-site variability. This study illustrates use of a new Bayesian Generalized Least Square (B-GLS) analysis (Reis et al., 2005) applied to the at-site estimators of L-CV and L-CS so as to partition the observed variation in estimated L-moment ratios between sampling and site-to-site variabilities, as well as to explore how much of the site-to-site variability can be explained by measured physiographic basin characteristics.

***Bayesian Generalized Least Square (B-GLS)***

Regional regression models have often been used to estimate distribution parameters (IACWD, 1982; Tasker and Stedinger, 1986; Madsen and Rosbjerg, 1997; Reis et al, 2005) as well as rainfall and flood quantiles for water resources planning and floodplain management. Estimates of the distribution parameters such as L-CV and L-CS at different gauged sites have different precision due to variations in record lengths and station estimates are generally spatially correlated. However, OLS (Ordinary Least Square) assumes the regression residuals to be homoscedastic and independently distributed in space. Stedinger and Tasker (1985, 1986) developed a GLS model that reflects both differences in record lengths and cross-correlations among station estimators. They showed that GLS provides better estimates of the model parameters and the model error variance in terms of mean square errors than does OLS. The GLS procedure has been widely recommended (Stedinger et al., 1993; World Meteorological Organization, 1994; Robson and Reed, 1999).

Reis et al. (2005) introduced a Bayesian analysis of the GLS model which provides both an exact measure of precision of the model error variance and a more reasonable description of the possible values of the model error variance in cases where the maximum-likelihood and method-of-moments model error variance estimators are zero or nearly zero. Our GLS analysis assumes that the actual value of the quantity of interest denoted $y_i$ (i.e. L-CV or L-CS) for a given site $i$ can be described by a function of physiographic characteristics with an additive error

 

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} + \delta_i \qquad i = 1, 2, \ldots, n \text{ stations} \tag{1}$$

wherein $X_{ij}$ ($j = 1\ldots, k$) is a matrix with explanatory variables describing the physical characteristics of each site $i$, and $\delta_i$ are the model errors which are assumed to be normal and independently distributed with model error variance $\sigma_\delta^2$. Unfortunately, only an at-site estimate of $y_i$, denoted as $\hat{y}_i$, is generally available. To described such data, a sampling error, denoted $\eta_i$, needs to be included in the model, so that

$$\hat{y}_i = y_i + \eta_i \qquad i = 1, 2, \ldots, n \text{ stations} \tag{2}$$

The variance of $\eta_i$ depends upon the length of record available at each site; they are also cross-correlated. Thus, the observed regression-model errors are a combination of: (i) time-sampling-error $\eta_i$ in the sample estimators of $y_i$ and (ii) underlying model error $\delta_i$. The value of $\sigma_\delta^2$ can be viewed as a heterogeneity measure (Madsen and Rosbjerg, 1997; Madsen et al., 2002).

Reis et al. (2005) computed the posterior moments of the parameters and the full posterior distribution of the model error variance $\sigma_\delta^2$. The examples showed that the Bayesian procedure provides a more reasonable description of the possible values of the model error variance, especially in cases where the sampling error variances are larger than the model error variance. The Bayesian approach requires the specification of prior distributions for both the regression parameters **b** and model error variance $\sigma_\delta^2$. A multivariate normal distribution with a mean of zero and a large variance was used for the prior for the parameters. This almost non-informative prior produces a pdf that is relatively flat in the region of interest. The prior information for the model error variance $\sigma_\delta^2$ was represented by an informative exponential distribution. As Reis et al. (2005) explain, this is a situation where a non-informative prior has problems because it will not be overwhelmed by the likelihood function.

***Model Diagnostic Measures***

Various diagnostic measures can be used to evaluate candidate models and select an appropriate model that fits the data and provides an accurate prediction, while keeping the model as simple as possible. When an interest is to make predictions at gauged and ungauged sites, the AVP (Average Variance of Prediction) can be used as the primary measure to evaluate likely model performance.

Given a site with basin characteristics $\mathbf{x}_0$, AVP describes how well a regional regression model estimates the true value of the quantity of interest, $y_0$, on average across sites such as those used in the regression analysis (Tasker and Stedinger, 1989). The AVP is computed as

$$AVP_{GLS} = \hat{\sigma}_\delta^2 + \frac{1}{N} \sum_{i=1}^{N} \mathbf{x}_i \left( \mathbf{X}^T \hat{\mathbf{\Lambda}}^{-1} \mathbf{X} \right)^{-1} \mathbf{x}_i^T \tag{3}$$

Here the $x_i$'s are the row vectors containing the physiographic characteristics of each site. When comparing regional regression models, a smaller AVP is preferred.

 

Within the Bayesian GLS framework, Reis et al. (2005) provides an expression for the posterior mean of the average variance of prediction for a new site.

Reis et al. (2006) also proposed a pseudo coefficient of determination ($R_{GLS}^2$) appropriate for use with GLS. The traditional adjusted-$R^2$ uses SSE and SST which both include the sampling and model error variances, and thus this statistic misrepresents the true power of GLS models to explain the actual variation in the $y_i$. A more appropriate pseudo coefficient-of-determination is -

$$\bar{R}^2_{GLS} = \frac{n[\hat{\sigma}^2_\delta(0) - \hat{\sigma}^2_\delta(k)]}{n\hat{\sigma}^2_\delta(0)} = 1 - \frac{\hat{\sigma}^2_\delta(k)}{\hat{\sigma}^2_\delta(0)} \tag{4}$$

where $\hat{\sigma}^2_\delta(k)$ and $\hat{\sigma}^2_\delta(0)$ are the model error variance estimates when $k$ and no explanatory variables are employed, respectively. $\bar{R}^2_{GLS}$ measures the improvement of a GLS regression model with $k$ explanatory variables against the estimated error varianice for a model without explanatory variables. If $\hat{\sigma}^2_\delta(k) = 0$, then $\bar{R}^2_{GLS} = 1$ as it should, even though the model is not perfect because Var[$\eta_i + \delta_i$] is still not zero because Var[$\eta_i$] > 0.

Other diagnostic statistics for GLS models are the EVR (Error Variance Ratio) and MBV (Misrepresentation of the Beta Variance), whose definitions are included in Table 3. (See also Reis et al. 2006; Griffis and Stedinger, 2006.) EVR is the ratio of the average sampling error variance to the model error variance. Thus large EVR values provide an indication of the need for a WLS or GLS analysis. When EVR is greater than 20%, one should employ a WLS or GLS as opposed to OLS analysis (Reis, 2005). MVB is the ratio of the variance GLS would compute for the constant term to the variance a WLS analysis would compute for the constant term in a WLS regression analysis (Griffis, 2006). MVB can be used to indicate whether a WLS analysis is sufficient, or if a full GLS analysis is needed. If MVB is substantially larger than 1, then the GLS estimate of the variance of the constant term will be that much larger than would be obtained with WLS.

Leverage and influence are also important tools in regression analyses because they help to identify rogue observations and lack of fit, and to select new sample locations. Tasker and Stedinger (1989) generalize measures of influence and leverage from the OLS case to WLS and GLS. They suggested influence is large when their influence statistic $D_i$ is greater than $4/n$ where $n$ is the number of sites, whereas leverage is large if greater than $2(k+1)/n$. In a Bayesian analysis, one needs to use the expected value of these quantities (Reis, 2005).

***Application***

B-GLS analyses developed models of the L-CV and L-CS across the entire southern Korean peninsula. The regional estimators of the L-CV and L-CS can be used to develop a parametric flood frequency distribution using the GEV (Generalized Extreme Value) distribution (Stedinger et al., 1993). Index variables for the three different major river basins (Han, Nakdong, and Geum & Seomjin basins), plus the logarithms of the drainage area (DA) and the channel slope (S) were considered as possible explanatory variables. This study tested all possible combinations of the explanatory variables. The prior distribution for the model error variance was exponential distribution with a mean of 1/100. Reis et al. (2005) discusses the choice of a prior for the model error variance.

The B-GLS analysis also requires estimating correlations among the annual maximum flows. Figure 2 shows sample correlations among concurrent annual maximum flows as a function of distance between stations in Korea. Only stations whose record lengths are greater than 22 years are included due to the high sampling variability for shorter periods of record. A line characterized by the following equation was fitted to approximate the sample correlation in Figure 2,

$$\rho_{xy} = \theta^{\left(\frac{d_{xy}}{\alpha d_{xy}+1}\right)} \tag{5}$$

where $\theta = 0.953$, $\alpha = 0.019$, and $d_{xy}$ represents the distance between two stations.

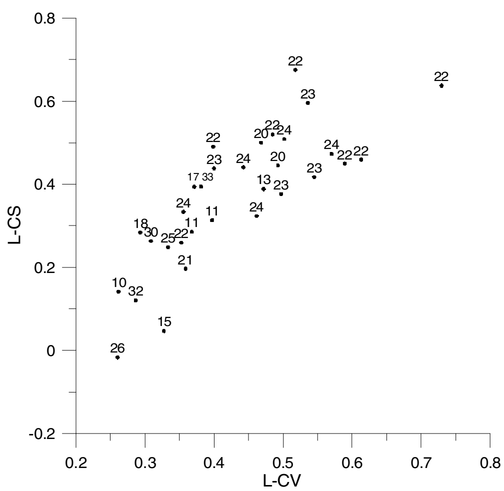


Figure 1. The sample L-CV and L-CS estimates of annual maximum flood data collected from 31 gauging stations in Korea. The number next to each dot reports the corresponding record length.

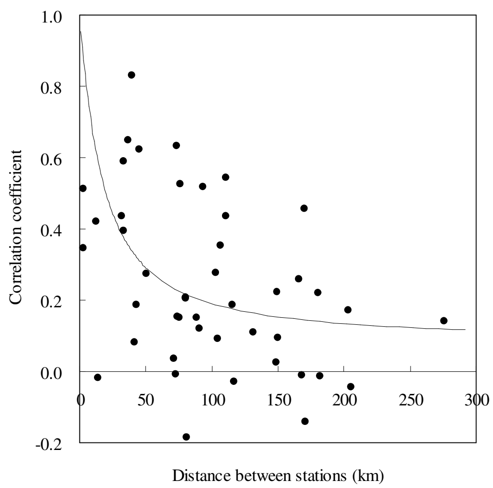


Figure 2. Correlations among concurrent annual maximum flows as a function of distance between stations in Korea. Only stations whose record length is greater than 22 years are considered.

Tables 1 and 2 compare the results of OLS, B-WLS, and B-GLS analyses of candidate models for L-CV and L-CS, respectively. The constant in the Tables essentially represents the regional mean for L-CV or L-CS because the explanatory variables were centered by subtracting their average value.

In both Tables, OLS produces larger model error variances and larger AVPs than WLS and GLS because OLS does not distinguish the modeling and the sampling errors. B-WLS results are very similar to the corresponding B-GLS results with respect to AVP and $R_{GLS}^2$, but here the model error variances are underestimated, especially for L-CS (for example, for B-WLS1 $\sigma_\delta^2$ = 0.0059 whereas for B-GLS1 $\sigma_\delta^2$ = 0.0073) because WLS does not account for the cross-correlations between sites. This concern is documented by the large value of MBV in Table 3.

As shown in Tables 1 and 2, B-GLS found that model 1 (denoted B-GLS1) that uses the drainage area as the only explanatory variable performs the best among the models consider; $AVP_{new}$ values for L-CV and L-CS are 0.007 and 0.010, respectively. Note that the modeling error represents 84% and 73% of $AVP_{new}$ for L-CV and L-CV, respectively. For L-CV, a B-WLS analysis would have selected model 3 as having the smaller $AVP_{new}$, as well as misrepresenting the value of $AVP_{new}$ as 0.0054 instead of the correct estimate of 0.0075.

The values of AVP imply that predicted L-CV and L-CS are equivalent in precision to at-site estimators calculated from approximately 16 and 44 years of record, respectively. These results indicate that the best regional model for L-CS (B-GLS1) is very useful because the effective record length of 44 years is twice the Korean average record length of 22 years; for L-CV the at-site estimator should be combined with the regional estimator whose effective record length of 16 years is shorter than the average sample record length, though longer than some records.

Table 1. Comparison of Best Candidate Models for L-CV

| **Model Name** | **Const.** | **$Z_1$ Han** | **$Z_2$ Nakdong** | **Ln(Area)** | **Model Error Variance** | **Average Sampling Variance** | **$AVP_{new}$** | **Pseudo $R^2$ (%)** | **ERL (years)** |
|---|---|---|---|---|---|---|---|---|---|
| OLS0 | 0.4314 | | | | 0.0127 | 0.0004 | 0.0131 | 0 | 8 |
| | (0.0203) | | | | | | | | |
| B-WLS0 | 0.4332 | | | | 0.0088 | 0.0004 | 0.0092 | 0 | 12 |
| | (0.0210) | | | | (0.0036) | | | | |
| B-GLS0 | 0.4153 | | | | 0.0076 | 0.0008 | 0.0084 | 0 | 13 |
| | (0.0279) | | | | (0.0031) | | | | |
| OLS1 | 0.4314 | | | -0.0360 | 0.0101 | 0.0007 | 0.0108 | 20 | 10 |
| | (0.0181) | | | (0.0123) | | | | | |
| | | | | (0.3 % ) | | | | | |
| B-WLS1 | 0.4327 | | | -0.0379 | 0.0058 | 0.0007 | 0.0065 | 33 | 17 |
| | (0.0186) | | | (0.0125) | (0.0028) | | | | |
| | | | | (0.4 %) | | | | | |
| B-GLS1 | 0.4194 | | | -0.0357 | 0.0059 | 0.0011 | **0.0070** | **22** | **16** |
| | (0.0268) | | | (0.0130) | (0.0025) | | | | |
| | | | | (0.8 %) | | | | | |
| OLS3 | 0.3484 | 0.1071 | 0.1192 | -0.0446 | 0.0083 | 0.0011 | 0.0094 | 35 | 12 |
| | (0.0334) | (0.0435) | (0.0445) | (0.0121) | | | | | |
| | | (1.4 %) | (0.7 %) | (0.0 %) | | | | | |
| B-WLS3 | 0.3544 | 0.1013 | 0.1149 | -0.0453 | 0.0043 | 0.0012 | 0.0054 | 51 | 20 |
| | (0.0340) | (0.0449) | (0.0456) | (0.0125) | (0.0025) | | | | |
| | | (2.6 %) | (1.4 %) | (0.1 %) | | | | | |
| B-GLS3 | 0.3384 | 0.1146 | 0.1101 | -0.0439 | 0.0054 | 0.0020 | 0.0075 | 28 | 15 |
| | (0.0452) | (0.0569) | (0.0602) | (0.0136) | (0.0023) | | | | |
| | | (4.5 %) | (6.7 %) | (0.2 %) | | | | | |

Table 2. Comparison of Best Candidate Models for L-CS

| Model Name | Const. | $Z_1$ Han | Ln(Area) | Model Error Variance | Average Sampling Variance | $AVP_{new}$ | Pseudo $R^2$ (%) | ERL (years) |
|---|---|---|---|---|---|---|---|---|
| OLS0 | 0.3679 | | | 0.0264 | 0.0009 | 0.0272 | 0 | 16 |
| | (0.0292) | | | | | | | |
| B-WLS0 | 0.3716 | | | 0.0085 | 0.0009 | 0.0094 | 0 | 47 |
| | (0.0299) | | | (0.0057) | | | | |
| B-GLS0 | 0.3402 | | | 0.0082 | 0.0018 | 0.0100 | 0 | 44 |
| | 0.0426 | | | (0.0050) | | | | |
| OLS1 | 0.3679 | | -0.0472 | 0.0221 | 0.0014 | 0.0235 | 16 | 19 |
| | (0.0267) | | (0.0181) | | | | | |
| | | | (0.9 %) | | | | | |
| B-WLS1 | 0.3705 | | -0.0492 | 0.0059 | 0.0016 | 0.0075 | 30 | 59 |
| | (0.0284) | | (0.0204) | (0.0016) | | | | |
| | | | (2.0 %) | | | | | |
| B-GLS1 | 0.3504 | | -0.0441 | 0.0073 | 0.0027 | **0.0100** | **11** | **44** |
| | (0.0423) | | (0.0204) | (0.0027) | | | | |
| | | | (2.0 %) | | | | | |
| OLS2 | 0.3107 | 0.1267 | -0.0638 | 0.0191 | 0.0019 | 0.0210 | 27 | 21 |
| | (0.0349) | (0.0541) | (0.0183) | | | | | |
| | | (1.9 %) | (< 0.01 %) | | | | | |
| B-WLS2 | 0.3166 | 0.1228 | -0.0646 | 0.0046 | 0.0022 | 0.0068 | 46 | 65 |
| | (0.0376) | (0.0619) | (0.0199) | (0.0041) | | | | |
| | | (3.6 %) | (0.2 %) | | | | | |
| B-GLS2 | 0.2863 | 0.1464 | -0.0563 | 0.0066 | 0.0039 | 0.0105 | 20 | 42 |
| | (0.0539) | (0.0777) | (0.0212) | (0.0042) | | | | |
| | | (6.0 %) | (0.8 %) | | | | | |

The performance of the best model identified by B-GLS (B-GLS1) for both L-CV and L-CS is further explored in Table 3 and Figures 3 and 4. The EVRs in Table 3 are 0.93 and 3.02 for L-CV and L-CS, respectively; clearly WLS or GLS should be employed instead of OLS, especially for L-CS for which the sampling error is three times as large as the model error.

MBVs in Table 3 are greater than 2 for both L-CV and L-CS, indicating cross-correlations among the L-CV and L-CS estimators should not be neglected; otherwise the estimated error of the constant in the model would be over a factor of two too small. This is critical when deciding whether to include indicator variables for different basin. Moreover, AVP would be underestimated as Tables 1 and 2 illustrate.

Figures 3 and 4 show the results of leverages and influences of the most influence sites sorted from largest influence. Among 31 sites, the site 16 has the largest influence for L-CV while the site 31 has the largest value for L-CS and the second largest for L-CV. Those two sites are included in both of Figures 3 & 4. Note the site 16 has the largest sample L-CV (0.73) and contains an extraordinary flood (1296 cms in 1987 whereas the median flood was just 21 cms). In the future site 31 may receive special treatment due to potential measurement error. Historical information may also help put such a value in content (Martin and Stedinger, 2001).

Table 3. Pseudo ANOVA table of B-GLS Model 1 for L-CV and for L-CS

| Source | Degrees-of-freedom | Sum of squares | | |
|---|---|---|---|---|
| | | Equations | L-CV | L-CS |
| Model | $k = 1$ | $n[\sigma_\delta^2(0) - \sigma_\delta^2(k)]$ | 0.051 | 0.029 |
| Model error $\delta$ | $n - k - 1 = 29$ | $n\sigma_\delta^2(k)$ | 0.184 | 0.226 |
| Sampling error $\eta$ | $n = 31$ | $\sum_{i=1}^{n} Var(\hat{y}_i)$ | 0.171 | 0.682 |
| Total | $2n - 1 = 61$ | $n\sigma_\delta^2(0) + \sum_{i=1}^{n} Var(\hat{y}_i)$ | 0.406 | 0.937 |
| $EVR = \frac{1}{n}\sum_{i=1}^{n} Var(\hat{y}_i) / \sigma_\delta^2(k)$ | | | 0.93 | 3.02 |
| $MBV = \frac{1}{n}\mathbf{w}^T \Lambda(\sigma_\delta^2)\mathbf{w}$, where **w** is the vector $(1/\sqrt{\Lambda_{ii}})$ | | | 2.15 | 2.30 |

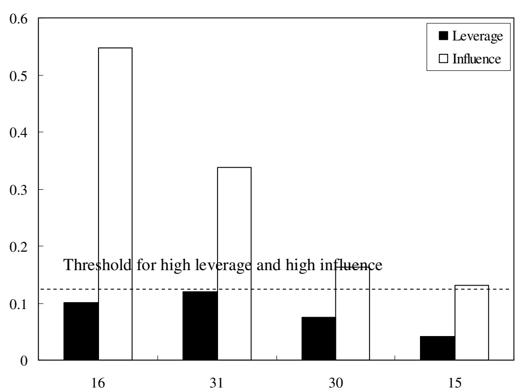


Figure 3. Leverage and influence in B-GLS Model 1 for L-CV

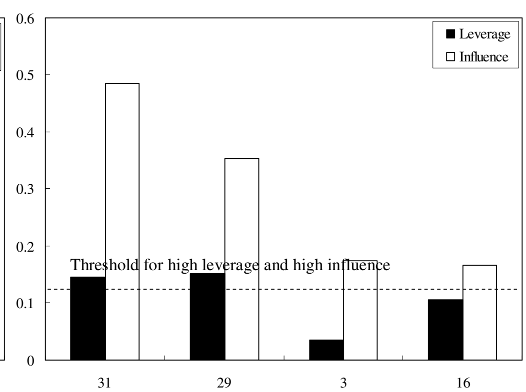


Figure 4. Leverage and influence in B-GLS Model 1 for L-CS

## *Conclusion*

Flood series in Korea are generally short and relatively sparse, and thus available data should be analyzed with care and with statistical efficient procedures. This study developed regression models for L-CV and L-CS for Korean annual maximum flood series using a Bayesian GLS analysis. The examples also illustrated the differences among OLS, B-WLS, and B-GLS analyses. Several useful diagnostic measures applied to the candidate models indicated that OLS overestimates the modeling error variance and the average sampling variance while B-WLS underestimates those variances. Using B-GLS, among the tested models for both L-CV and L-CS, the model that employs only the drainage basin as an explanatory variable had the smallest prediction error as measured by the expected average variance of prediction for a new site. Given the precision of these regional estimators and available record lengths in Korea, this study suggests that a regional estimator for L-CV (effective record length 16 years) should be combined with its at-site estimator, while the regional estimator for L-CS (effective record length 44 years) is relatively precise and can serve as the a good estimator of shape in a flood frequency studies. These numbers are of course just estimates based on the available data at 31 sites.

Overall the Bayesian Generalized Least Squares framework allowed for a careful and statistically efficient analysis of the data that demonstrated the need for a GLS analysis, that found the best predictive model and its precision, and which identified rogue observations in the dataset.

***Acknowledgements***

We thank to Andrea Gruber and Dirceu Reis who shared their ideas and analysis methods with us. This study was supported by the 2005 SOC Project (05-GIBANGUCHUK-D03-01) through the Design Criteria Research Center for Abnormal Weather-Disaster Prevention (DCRC-AWDP) in KICTTEP of MOCT, KOREA.

***References***

Fill, H. D., and Stedinger, J. R. (1998). "Using regional regression within index flood procedures and an empirical Bayesian estimator." *J. of Hydrology*, 210(1-4), 128-145.

Griffis, V. W. (2006). *Flood frequency analysis: Bulletin 17, regional information, and climate change*, Ph.D. dissertation, Cornell University, Ithaca, NY.

Griffis, V. W., and Stedinger, J. R. (2006) "The use of GLS regression in regional hydrologic analyses." manuscript, Cornell University.

Hosking, J. R. M., and Wallis, J. R. (1997). *Regional frequency analysis: An approach based on L-Moments,* Cambridge University Press, UK.

Interagency Advisory Committee on Water Data (IACWD). (1982). "*Guidelines for Determining Flood Flow Frequency*, Bulletin 17B (revised and corrected)." U.S. Department of the Interior, U.S. Geological Survey, Office of Water Data Coordination, Reston, Virginia, 1982.

Madsen, H., and Rosbjerg, D. (1997). "Generalized least squares and empirical Bayes estimation in regional partial duration series index-flood modeling," *Water Resour. Res.*, 33(4), 771-782.

Madsen, H., and Rosbjerg, D. (1997). "Generalized least squares and empirical Bayes estimation in regional partial duration series index-flood modeling." *Water Resour. Res.*, *33*(4), 771-782.

Madsen, H., Mikkelsen, P. S., Rosbjerg, D., and Harremoe¨s, P. (2002). "Regional estimation of rainfall intensity-duration-frequency curves using generalized least squares regression of partial duration series statistics." *Water Resour.*

*Res.*, 38(11), 1239, doi:10.1029/2001WR001125.
Martins, E.S., and Stedinger, J. R. (2001). "Historical information in a GMLE-GEV framework with partial duration and annual maximum series." *Water Resour. Res.* 37(10), 2551-2557.
Ministry of Construction & Transportation (MOCT) (2001). *National water resources plan*, MOCT, Korea (in Korean).
National Research Council (1988). *Estimating probabilities of extreme floods: methods and recommended research*, National Academy Press, Washington, DC.
Reis, D. S., Jr. (2005). *Flood frequency analysis employing Bayesian regional regression and imperfect historical information*, Ph.D. dissertation, Cornell University, Ithaca, NY.
Reis, D. S., Jr., Stedinger, J. R., and Martins, E. S. (2005). "Bayesian generalized least squares regression with application to log Pearson type 3 regional skew estimation." *Water Resour. Res.*, 41, W10419, doi:10.1029/2004WR003445.
Reis, D. S., Jr., Stedinger, J. R., and Martins, E. S. (2006). "Operational Bayesian GLS Regression for Regional Hydrologic Analyses." manuscript, Cornell University.
Robson, A. J., and Reed, D. W. (1999). *Flood estimation handbook*, vol. 3, Statistical Procedures for Flood Frequency Estimation, Inst. Of Hydrol., Wallingford, U.K.
Stedinger, J. R., and Lu, L. (1995). "Appraisal of regional and index flood quantile estimators." *Stochastic Hydrology and Hydraulics*, 9(1), 49-75.
Stedinger, J. R., and Tasker, G. D. (1985). "Regional hydrologic analysis, 1. Ordinary, weighted and generalized least squares compared." *Water Resour. Res.*, 21(9), 1421-1432.
Stedinger, J. R., and Tasker, G. D. (1986). "Regional hydrologic analysis, 2: Model-error estimators, estimation of sigma and log-Pearson Type 3 distributions." *Water Resour. Res.*, 22(10), 1487-1499.
Stedinger, J. R., Vogel, R. M., and Foufoula-Georgiou, E., (1993). "Frequency analysis of extreme events." *Handbook of Hydrology*, Chap. 18, pp. 18.1-18.66, McGraw-Hill Book Co., NY.
Tasker, G. D., and Stedinger, J. R. (1989). "An operational GLS model for hydrologic regression." *J. of Hydrology*, 111(1-4), 361-375.
Tasker, G. D., and Stedinger, J.R. (1986). "Estimating generalized skew with weighted least squares regression." *J. of Water Resources Planning and Management*, 112(2), 225-237.
World Meteorolgical Organization (1994). *Guide to hydrological practices, data acquisition and processing, analysis, forecasting and other applications*, WMO, Rep. 168, Geneva, Switzerland.