

Provided for non-commercial research and education use.  
Not for reproduction, distribution or commercial use.

## Climate informed flood frequency analysis and prediction in Montana using hierarchical Bayesian modeling

Hyun-Han Kwon,<sup>1,2</sup> Casey Brown,<sup>3</sup> and Upmanu Lall<sup>1,3</sup>

Received 9 October 2007; revised 29 November 2007; accepted 4 January 2008; published 8 March 2008.

[1] It is widely acknowledged that climate variability modifies the frequency spectrum of extreme hydrologic events. Traditional hydrological frequency analysis methods do not account for year to year shifts in flood risk distributions that arise due to changes in exogenous factors that affect the causal structure of flood risk. We use Hierarchical Bayesian Analysis to evaluate several factors that influence the frequency of extreme floods for a basin in Montana. Sea surface temperatures, predicted GCM precipitation, climate indices and snow pack depth are considered as potential predictors of flood risk. The parameters of the flood risk prediction model are estimated using a Markov Chain Monte Carlo algorithm. The predictors are compared in terms of the resulting posterior distributions of the parameters that are used to estimate flood frequency distributions. The analysis shows an approach for exploiting the link between climate scale indicators and annual maximum flood, providing impetus for developing seasonal forecasting of flood risk applications and dynamic flood risk management strategies. **Citation:** Kwon, H.-H., C. Brown, and U. Lall (2008), Climate informed flood frequency analysis and prediction in Montana using hierarchical Bayesian modeling, *Geophys. Res. Lett.*, 35, L05404, doi:10.1029/2007GL032220.

### 1. Introduction

[2] Climate is continuously changing and the signature of change is evident in historical hydrology records and rainfall patterns [Knox, 1993]. The most prominent example of interannual climate variability, El Niño-Southern Oscillation (ENSO), has been extensively investigated for its effects on hydrologic variables [Piechota and Dracup, 1996; Ropelewski and Halpert, 1986, 1987]. Mounting evidence demonstrates that climate variability also modifies the frequency of extreme hydrologic events [Franks and Kuczera, 2002; Jain and Lall, 2000, 2001; Milly et al., 2002; Pizaro and Lall, 2002]. Porparto and Ridolfi [1998] demonstrate that natural and often predictable variability produces significant changes in flood frequencies. For example, large floods at a given site may be related to large scale atmospheric circulation anomalies [Hirschboeck, 1988; Knox, 1993]. These processes are part of a climatic framework that influences the large-scale delivery pathways

of atmospheric moisture, and their seasonal variations, typical locations, degree of persistence, and seasonal variation of climate-related, land-surface conditions such as antecedent soil moisture or snow cover. In addition, large scale circulation anomalies such as the Pacific Decadal Oscillation (PDO) and the Northern Atlantic Oscillation (NAO), which exhibit low frequency modes, may result in decadal scale variability in flood risk [Olsen et al., 1999].

[3] Water resources managers are challenged by the dawning recognition of nonstationarity in the frequency distribution of extreme hydrologic events. While the impact of climate variability on flood risk is acknowledged, the use of this information, such as for seasonal forecasts of flood risk and incorporation in flood management methodology remains rare. Increased knowledge of climate influences on flood events, and the demonstrable nonstationarity of flood time series are the theoretical basis for the development of a flood event probability function dependant on climate states. A common illustration is the shift in flood occurrence probability during an ENSO event in many parts of the world [Khalil et al., 2007]. The existing techniques for flood frequency analysis regard the time series of annual maximum floods as stationary, which in practice leads to an implicit assumption that the distribution of floods is not significantly affected by climatic conditions [Olsen et al., 1999]. However, observed flood records that exhibit cycles, secular trends and low frequency variability provide evidence that the stationarity assumption is not valid in many cases [Jain and Lall, 2000, 2001]. Furthermore, cyclical modes of variability in the frequency spectrum of hydrologic variables invalidate the common practice of treating hydrologic variables independently from the frequency of their generating mechanisms. In fact, they introduce the potential for prediction.

[4] Previous studies have modeled the impact of exogenous (to the flow record) variables on flood risk. A simple linear regression of flood on time was studied by Olsen et al. [1999]. Climate indices (Nino3 and PDO) were evaluated using a parametric quantile regression approach and a semiparametric local likelihood approach on synthetic data sets and for data from a streamflow gauging station in Montana [Sankarasubramanian and Lall, 2003]. This study builds from that approach, comparing available surface and climate data as predictors of annual flood risk. In the present study, Hierarchical Bayesian modeling is used to estimate the mean values and uncertainty distributions of the parameters of the flood frequency distribution.

[5] A brief summary of the main concept of this study is presented in this section. In section 2, the data set used to illustrate the method and the climate informed flood frequency analysis model are introduced. The application of Hierarchical Bayesian modeling for the estimation of

<sup>1</sup>Department of Earth and Environmental Engineering, Columbia University, New York, New York, USA.

<sup>2</sup>Now at Water Resources Research Division, Korea Institute of Construction Technology, Goyang, South Korea.

<sup>3</sup>International Research Institute for Climate and Society, Columbia University, Palisades, New York, USA.

the parameters of the extreme event (flood) frequency distribution model is described in section 3. In section 4, the proposed model is applied to a time series of annual maximum floods in Montana. Results are discussed in section 5 and the paper closes with conclusions in section 6.

## 2. Data

[6] The premise of this study is that climate information can reduce the uncertainty in flood risk for a given year that results due to climate variability and nonstationarity. The analysis utilizes historical flood data, global SSTs, snow pack and GCM prediction rainfall. An application of the climate informed flood frequency analysis was performed with data from the gauge at Clark Fork River (USGS Station No: 12353000) in Montana; the same gauge was used by *Sankarasubramanian and Lall* [2003]. Daily streamflow records are available from 1930 to present. The annual (calendar year) maximum streamflow, which occurs during May–June–July, was the target variable. Since a primary objective of this study is to examine the predictability of the extreme flood events given relevant predictors, season ahead (Feb–Mar–Apr) values for SSTs, GCM output and snow pack data were used. We use a gridded SST product of  $5^\circ \times 5^\circ$  monthly anomalies from 1856-present [*Kaplan et al.*, 1998]. Global monthly SSTs were transformed to seasonal SSTs and FMA were retained for analysis. For snow pack, eleven snow stations near the streamflow station are available from 1930–2005, and these data was spatially averaged over the stations creating a snowpack index. The monthly snow data (Jan–Apr) were then transformed to seasonal mean snowpack. The GCM product evaluated in this study is the atmospheric general circulation model ECHAM4.5 FMA seasonal precipitation forecast [*Roeckner et al.*, 1996]. For ENSO, the Nino3 index was derived from the *Kaplan et al.* [1998] SST dataset, while for PDO the index defined by *Zhang et al.* [1997] was used.

## 3. Climate Informed Flood Frequency Analysis Using Hierarchical Bayesian Model

[7] A Hierarchical Bayesian-based climate informed flood frequency analysis model is proposed to accommodate climate variability and nonstationarity using time-dependent climate predictors. An objective of Bayesian methods is to compute the posterior distribution of the desired variables, in this case the parameters of the annual maximum flood distribution. The posterior distribution of the parameter vector,  $\theta$ , is  $p(\theta|x)$ , given by Bayes Theorem as follow:

$$p(\theta|x) = \frac{p(\theta) \times p(x|\theta)}{p(x)} = \frac{p(\theta) \times p(x|\theta)}{\int_{\Theta} p(\theta) \times p(x|\theta) d\theta} \propto p(\theta) \times p(x|\theta) \quad (1)$$

where  $\theta$  is the vector of parameters of the distribution to be fitted,  $\Theta$  is the space parameter,  $p(\theta|x)$  is the likelihood function,  $x$  is the vector of observations and  $p(\theta)$  is the prior distribution. Here, we present a method for incorporating climate information into updated estimates of the parameters for the extreme value distribution used to represent

the annual maximum flood. The model is expressed in terms of both a location parameter  $\mu(t)$  and a scale parameter  $\sigma(t)$ , which both change with time,  $t$ . The parameters are hypothesized to be functions of climate indicators, such as SST, snowpack and GCM output that are developed here and others, such as ENSO and PDO, that are generally recognized climate phenomena with expected local impacts.

[8] Using the Gumbel extreme type distribution, the distribution of annual peak flood  $Z(t)$  can be modeled as follows:

$$Z(t) \sim \text{Gumbel}(\mu(t), \sigma(t)) \quad (2)$$

[9] In the present case the standard deviation,  $\sigma(t)$ , was not found to vary significantly as a function of time. As a result, equation (2) is changed as follows:

$$Z(t) \sim \text{Gumbel}(\mu(t), \sigma) \quad (3)$$

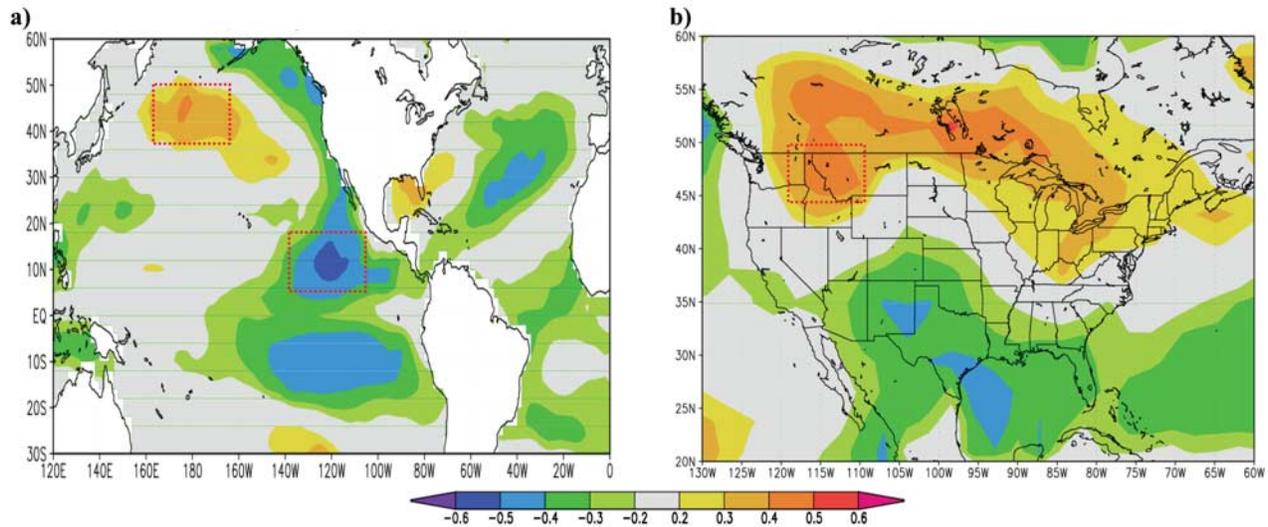
$$\mu(t) = \beta_0 + \beta_1 \mathbf{X}_1(t) + \dots + \beta_k \mathbf{X}_k(t) \quad (4)$$

where  $\mathbf{X}_i$ , climate indices, are the  $i$ th rows of the known design matrices  $\mathbf{X}$ , and  $\beta$  is a vector of regression parameters. The Bayesian approach allows us to carry through the uncertainty associated with each parameter to the final estimated value (in this case peak annual flood). In order to do so, each parameter must be assigned a distribution that reflects our prior belief of that parameter value. The parameters are then fit through sampling from these distributions to maximize the likelihood under the model, in this case the Gumbel distribution. Here, we assume the regression parameters,  $\beta$ , are normally distributed,  $\beta_k \sim N(\eta_{\beta k}, \sigma_k)$ . The parameters of this distribution, or hyperparameters,  $\eta_{\beta k}$  and  $\sigma_k$ , are also assigned distributions that reflect our prior beliefs regarding their values. We assign a zero mean normal distribution for  $\eta_{\beta k}$  ( $\eta_{\beta k} \sim N(0.0, \sigma_{\beta k})$ ) and half-Cauchy distributions for  $\sigma_k$ , and  $\sigma_{\sigma k}$  to constrain them to positive values [*Gelman*, 2006].

[10] The parameters described above are fit simultaneously using WinBUGS [*Lunn et al.*, 2000]. The software employs the Gibbs sampler, a Markov Chain Monte Carlo (MCMC) method for simulating the posterior probability distribution of the data field conditional on the current choice of parameters [*Gelman*, 2006]. The Gibbs sampler explores the multivariate parameter space by fixing all but one of the parameters, sampling from the conditional distribution of the unfixed parameter and then repeating for the next parameter. The conditional distribution is conditioned on the fixed values of the other parameters. Most statistical applications of MCMC methods use the Gibbs sampler. For further reading on the use of MCMC methods for Bayesian inference, and specifically the Gibbs Sampler, see [*Gilks et al.*, 1995].

## 4. Application of Nonstationary Flood Model to Montana Time Series

[11] There exists an interesting relationship between the annual maximum flood series of the western U.S. and PDO and ENSO indices and other SST patterns that persists despite differences in flood mechanism, drainage area and season of occurrence [*Pizaro and Lall*, 2002]. This suggests



**Figure 1.** (a) Correlation map between a flood series and a FMA seasonal SST from 1930 to 2005. (b) Relationship between a flood series and a predicted GCM FMA precipitation from 1958 to 2005. The areas chosen as predictors are indicated by boxes. An index for each was constructed using the spatial average of the variable over the box area.

that ocean-atmosphere-land hydrologic processes associated with the annual maximum may have predictability that is conditional on the climate state.

[12] In a previous study, *Sankarasubramanian and Lall* [2003] used the winter averages of the NINO3 and PDO indices as the predictors of extreme floods measured at the Clark Fork River, MT, the same gauge used in this study. These correlations with the flood series were statistically significant, and continue to be so as confirmed by this study. The flood season at this location is predominantly May–June–July with peak flows occurring primarily in June. In order to assess predictability of flood risk, predictors available only in the preceding season were used and 27 years of data are held out for cross-validation. First, global SSTs (February–March–April, FMA) from 1930 to 2005 were evaluated as predictors. The spatial pattern of correlations with the flood series is displayed in Figure 1a. This figure shows that anomalous conditions in SSTs are likely to strongly influence the annual maximum peak. While it exhibits patterns of correlations reflecting ENSO (equatorial Pacific) and PDO (extratropical North Pacific) as expected, it is notable that the strongest correlations are outside these two regions. This region is similarly implicated in a study of the influence of SST anomalies on summer drought in the US West [*Rajagopalan et al.*, 2000]. In the present study, Principal Component Analysis (PCA) was applied to the common signal from two SST zones with highest correlations (160E–200E, 37N–50N; 230E–250E, 5N–20N) and the first PC retained as the predictor.

[13] The largest flow volumes in Montana streams usually occur during the spring and early summer months with the

melting of the winter snowpack. The mechanisms for peak values are heavy rains falling during the spring thaw of a large snowpack. Here we evaluate the influence of the preceding snowpack in the region of the streamflow station. The preceding mean snowpack index from 1937 to 2005 is used as a predictor in the model.

[14] The final predictor used for flood risk estimation is model output from the ECHAM 4.5 GCM. The ability of GCM output to predict important hydrologic variables such as annual flood risk on seasonal timescales may guide the use of such output for estimations of future flood risk under climate change scenarios. For this reason, we evaluate the ability of GCM output to predict annual maximum streamflow. Winter (FMA) precipitation is used because of the high skill achieved using observed snowpack. Figure 1b shows the map of correlation results between peak annual flood and the season ahead forecast of precipitation from the model. Results are moderately encouraging. The GCM output spatially averaged over the box shown in the figure is statistically significantly correlated at the 95% confidence level, at levels similar to values for Nino3 and PDO indices (see Table 1).

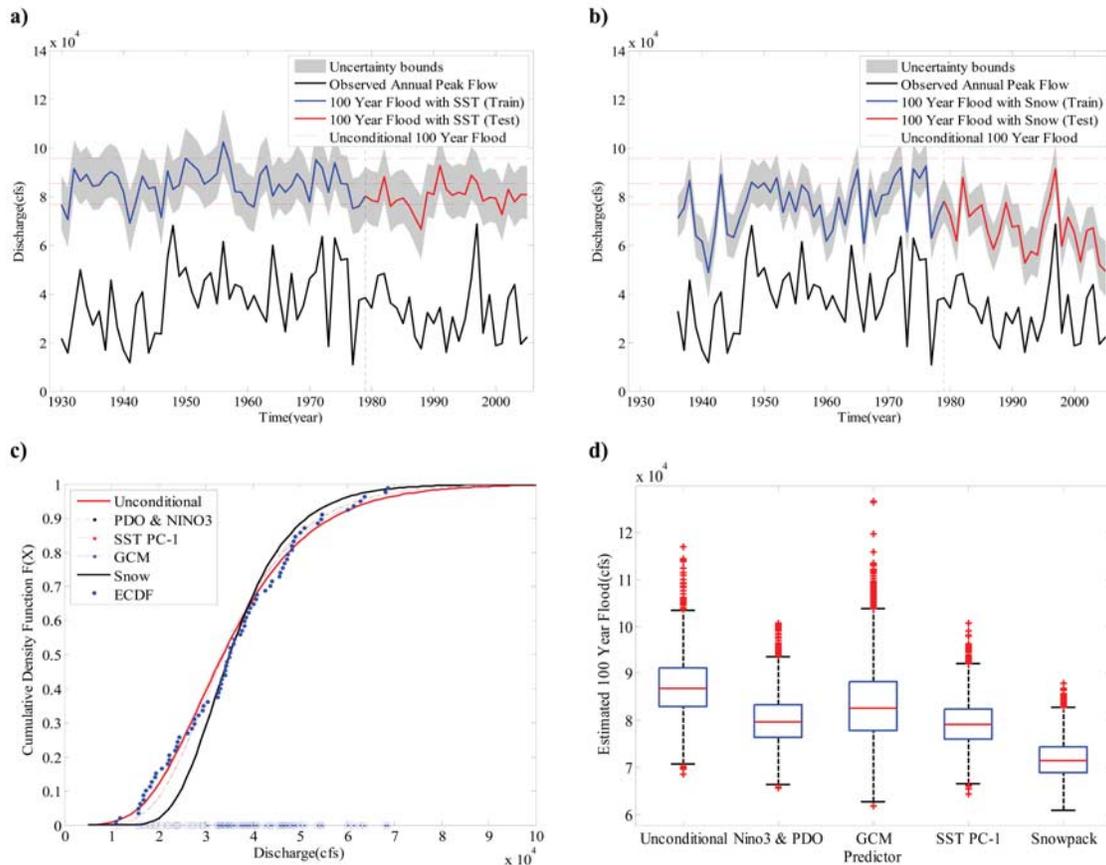
### 5. Results

[15] The variability of the annual maximum flood on the Clark Fork River is apparent in the time series depicted in Figure 2. In addition to the stochastic nature of extreme events, there is evidence that the flood time series is influenced by climate anomalies, that is, persistent anomalous conditions of climatologic variables such as SSTs at seasonal or longer timescales. Table 1 shows correlation

**Table 1.** Correlation Coefficients With P-Values Between the Annual Maximum Flood Series and Climate Indices<sup>a</sup>

	Nino3	PDO	Snow Pack	SST PC1	GCM
Period	1930–2005	1930–2005	1937–2005	1930–2005	1958–2005
Corr. Coeff.	–0.39†	–0.44†	0.78†	0.49†	0.45†
P-Value	0.001	0.000	0.000	0.000	0.005

<sup>a</sup>The null hypothesis of zero correlation is rejected at the 5%(†) significance level for each of these estimates.



**Figure 2.** Climate informed estimate of the 100-year return period flood with (a) SST predictor and (b) snow predictor. The model estimation is performed in a cross-validation mode by dropping data from 1979 to 2005. Blue (training period) and red (validation period) solid lines show the estimated value of the 100-year flood for each predictor. The stationary (unconditional) estimate of the 100 year flood based on the full historical record and its confidence interval (5% and 95%) is indicated by red dotted lines. The correlation coefficient between observed peak flow and predicted is shown on each figure for the training period and validation period. Unconditional estimates of the 100 year flood are displayed in the form of (c) the cumulative density function and (d) the mean estimate of the 100 year return period flood based on the pooled values of the yearly estimates conditioned on each predictor.

statistics between the flood series and four indicators of anomalous climate conditions and one GCM estimate of seasonal climate (precipitation). Each is statistically significant at the 95% confidence level. The highest value is with the snowpack depth observation, followed by the value with the first principal component of the signal from the SST zones.

[16] Each of the climate indicators (including the GCM precipitation forecast) was evaluated as a predictor of the annual peak flow. The hierarchical Bayesian model was used to estimate the regression parameters of equation (4). The regression equations (developed separately for each predictor) were then used to estimate the mean of the extreme value distribution function for each year conditioned on each predictor. The regression parameters for each predictor are shown in Table 2. Bayesian estimation of the parameter values yields a posterior distribution for each regression parameter. In Table 2, we report the mean and standard deviation of the posterior distribution for each regression parameter. Four models are reported: a PDO and ENSO index model; an SST model; a GCM model

and a snowpack model. Note that uncertainty bands are smallest for the snowpack and the SST predictors.

[17] Estimates of the peak flood value with 1% probability of occurring in a given year (100 year flood) were produced for each year using the Bayesian extreme value distribution model conditioned on the value of each predictor for that year. These time series are shown in Figure 2 along with the observed values of annual peak flood. The model estimation is performed in a cross-validation mode by dropping data from 1979 to 2005 with a confidence interval (5% and 95%) derived by stationary flood frequency analysis. The model shows very good skill in predicting year to year variability in flood risk, with a correlation between observed and predicted peak annual flow of 0.70 and 0.5 for snow and the SST predictor, respectively. These results compare favorably with *Sankarasubramanian and Lall* [2003], which used a parametric quantile regression approach and a semiparametric local likelihood approach to predict peak flow at the same location. The previous study presented a correlation of 0.5 between the conditional flood quantiles and the observed annual maximum peak. In addition to comparable prediction

**Table 2.** Posterior Estimates of the Regression Parameter Values for Equation (4) Which Estimates the Mean of the Gumbel Distribution Conditional on Each of the Predictors Listed Below<sup>a</sup>

Predictor	Parameters	Mean	SD	2.50%	Median	97.50%
PDO & NINO3	Intercept	30120	1276	27600	30130	32670
	PDO	-4327	1669	-7649	-4326	-1045
	Nino3	-3770	2149	-7911	-3824	681
SST PC-1	Intercept	29660	1291	26880	29700	32330
	SST PC-1	6145	1302	3641	6114	8706
GCM	Intercept	30010	1914	26180	30040	33870
	GCM	21460	9900	1553	21750	40070
Snow	Intercept	-14580	4676	-23540	-14350	-6185
	Snow	1072	107	876	1070	1281

<sup>a</sup>The mean, standard deviation, and confidence intervals for each regression parameter ( $\beta_k$ ) are listed.

skill, the present study provides an estimate of the relative uncertainty associated with each prediction, which allows us to assess whether the interannual variability falls outside the expected range of the unconditional estimate. The prediction model based on snow performed best. While not presented here, additional analysis showed combining predictors added little to model performance, a result of the correlation between predictors.

[18] Interestingly, it was found that the conditional predictions of the 100 year flood fell outside the confidence intervals of the unconditional estimate, an indication of nonstationarity in flood risk. This evidence suggests that an unconditional estimate of a design flood may be significantly different than the true flood risk in a given year, a cautionary note for traditional design methods.

[19] Next, the unconditional 100 year flood (i.e., the estimate of the flood based on the full record of historical peak flows, not conditioned on the value in a particular year) was estimated for the Clark Fork River using the observed time series and the extreme value distributions that resulted from the parameter estimations based on the climate predictors. The parameters of the Gumbel distributions for each predictor are estimated, and the resulting cumulative distribution functions are shown in Figure 2c. The results, including uncertainty bands, are shown in Figure 2d. Note the reduction of uncertainty when climate predictors are included, as well as the decrease in the flood risk as estimated by the predictors, most notably the snowpack depth index. Whereas reduction in snowpack may be linked to secular temperature trends, PDO and ENSO indices also appear to influence flood risk. The reduced flood risk predicted by these indicators may result from incomplete sampling of low frequency climate influences on flood risk.

## 6. Conclusions

[20] This study investigated use of a Bayesian hierarchical model to estimate annual flood risk based on climate indicators in comparison with traditional flood risk estimation. The results demonstrate statistically significant links to SST indices, snowpack depth and GCM season-ahead forecasts of precipitation. The Bayesian hierarchical model allowed estimation of uncertainty bands for model parameters and flood risk estimates and detection of nonstationarity in flood risk. Used in prediction mode, the climate indicators exhibited the ability to capture year to year variations in flood risk and to provide a reduction in the uncertainty accompanying the estimated value of the 100 year flood. In addition, in several years the conditional estimate of

flood risks fell outside the uncertainty bounds of the traditional (unconditional) estimate, an indication of nonstationarity in flood risk at this location. There are two important implications of this work. First, forecasts of changes in the risk associated with the peak annual flood may provide value for reservoir managers and provide some impetus for managing flood risk dynamically, consistent with its variable nature. Second, reduced uncertainty in the estimation of the 100 year flood, typically used as a design value in engineering, reduces the potential costs of over- and under-design of flood mitigation infrastructure and land use planning.

[21] **Acknowledgments.** This paper is funded by a grant/cooperative agreement from the National Oceanic and Atmospheric Administration (NOAA), NA05OAR4311004. The views expressed herein are those of the author(s) and do not necessarily reflect the views of NOAA or any of its sub-agencies.

## References

- Franks, S. W., and G. Kuczera (2002), Flood frequency analysis: Evidence and implications of secular climate variability, New South Wales, *Water Resour. Res.*, 38(5), 1062, doi:10.1029/2001WR000232.
- Gelman, A. (2006), Prior distributions for variance parameters in hierarchical models, *Bayesian Anal.*, 1, 515–533.
- Gilks, W. R., et al. (1995), Adaptive rejection metropolis sampling within Gibbs sampling, *J. R. Stat. Soc., Ser. C*, 44, 455–472.
- Hirschboeck, K. K. (1988), Flood hydroclimatology, in *Flood Geomorphology*, pp. 27–50, John Wiley, New York.
- Jain, S., and U. Lall (2000), Magnitude and timing of annual maximum floods: Trends and large-scale climatic associations for the Blacksmith Fork River, Utah, *Water Resour. Res.*, 36, 3641–3651.
- Jain, S., and U. Lall (2001), Floods in a changing climate: Does the past represent the future?, *Water Resour. Res.*, 37, 3193–3205.
- Kaplan, A., M. A. Cane, Y. Kushnir, A. C. Clement, M. B. Blumenthal, and B. Rajagopalan (1998), Analyses of global sea surface temperature 1856–1991, *J. Geophys. Res.*, 103, 18,567–18,589.
- Khalil, A. F., H.-H. Kwon, U. Lall, M. J. Miranda, and J. Skees (2007), El Niño–Southern Oscillation–based index insurance for floods: Statistical risk analyses and application to Peru, *Water Resour. Res.*, 43, W10416, doi:10.1029/2006WR005281.
- Knox, J. C. (1993), Large increases in flood magnitude in response to modest changes in climate, *Nature*, 361, 430–432.
- Lunn, D. J., A. Thomas, N. Best, and D. Spiegelhalter (2000), WinBUGS—A Bayesian modelling framework: Concepts, structure, and extensibility, *Stat. Comput.*, 10, 325–337.
- Milly, P. C. D., et al. (2002), Increasing risk of great floods in a changing climate, *Nature*, 415, 514–517.
- Olsen, J. R., et al. (1999), Climate variability and flood frequency estimation for the Upper Mississippi and Lower Missouri Rivers, *J. Am. Water Resour. Assoc.*, 35, 1509–1523.
- Piechota, T. C., and J. A. Dracup (1996), Drought and regional hydrologic variation in the United States: Associations with the El Niño Southern Oscillation, *Water Resour. Res.*, 32, 1359–1373.
- Pizaro, G., and U. Lall (2002), El Niño and floods in the US west: What can we expect?, *Eos Trans. AGU*, 83, 349.
- Porparto, A., and L. Ridolfi (1998), Influence of weak trends on exceedance probability, *Stochastic Hydrol. Hydraul.*, 12, 1–15.

- Rajagopalan, B., et al. (2000), Spatiotemporal variability of ENSO and SST teleconnections to summer drought over the United States during the twentieth century, *J. Clim.*, *13*, 4244–4255.
- Roeckner, E., et al. (1996), The atmospheric general circulation model ECHAM4: Model description and simulation of present-day climate, *Rep. 218*, 90 pp., Max Planck Inst. fur Meteorol., Hamburg, Germany.
- Ropelewski, C. F., and M. S. Halpert (1986), North-American precipitation and temperature patterns associated with the El Nino Southern Oscillation (ENSO), *Mon. Weather Rev.*, *114*, 2352–2362.
- Ropelewski, C. F., and M. S. Halpert (1987), Global and regional scale precipitation patterns associated with the El-Nino Southern Oscillation, *Mon. Weather Rev.*, *115*, 1606–1626.
- Sankarasubramanian, A., and U. Lall (2003), Flood quantiles in a changing climate: Seasonal forecasts and causal relations, *Water Resour. Res.*, *39*(5), 1134, doi:10.1029/2002WR001593.
- Zhang, Y., J. M. Wallace, and D. S. Battisti (1997), ENSO-like interdecadal variability: 1900–93, *J. Clim.*, *10*, 1004–1020.
- 
- C. Brown, International Research Institute for Climate and Society, Columbia University, 61 Route 9W, Monell Building, Palisades, New York, USA. (caseyb@iri.columbia.edu)
- H.-H. Kwon, Senior Researcher, Water Resources Research Division, Korea Institute of Construction Technology, Daehwa-Dong, Ilsan-Gu, Goyang-Si, Gyeonggi-Do, South Korea 411-712.
- U. Lall, Department of Earth and Environmental Engineering, Columbia University, 918 Mudd, 500 W 120th Avenue, New York, NY 10027, USA.