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Flood Frequency Estimation by Neyman-Scott Rectangular Pulse Rainfall Model and TOPMODEL

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A spatial-temporal Neyman-Scott Rectangular Pulse (NSRP) stochastic rainfall model is developed for seasonal-continuous simulation to project annual discharge probabilities from a relatively small watershed, the 1395 km^2 Upper Iowa River watershed upstream from Decorah, Iowa. NSRP rainfall data is used as rainfall input to TOPMODEL, a conceptual, semi-distributed rainfall runoff model, to calculate river discharge at a site common to the United States Geological Survey (USGS) gauging station in Decorah, Iowa. Annual peak flows based on simulated rainfall are used to fit a log-Pearson type III distribution to project 1%-, 0.2%-, and 0.1%-annual discharges. These results are compared to projections for the same frequency flows based on observed annual peak flow data measured at the USGS gauge site in Decorah. The NSRP model parameters are modified to reflect changes in environmental storm parameters (e.g. rainfall intensity and storm frequency) due to a warming atmosphere to study the sensitivity of annual peak flows due to climate variations.

INDEX DESCRIPTORS: stochastic rainfall model, rainfall runoff, flood frequency, climate sensitivity.

The Upper Iowa River begins near the city of Leroy in southern Minnesota and winds its way through several counties of northeast Iowa before reaching the Mississippi River near the Iowa-Minnesota border. Decorah, Iowa is situated along the banks of the Upper Iowa River, about two-thirds the way from the source to the mouth. The Army Corp of Engineers constructed a levee in the late 1940's to protect Decorah from frequent floods. The peak flow of 937 in m^{3}s^{-1} June of 2008 is the largest on record (annual peak flows are recorded or accurately calculated for 87 years beginning in 1914). The high-water mark in 2008 was approximately 30 cm below the top of the levee. The annual exceedance probability of such a flow is well below 0.001 (the so-called "1000-year flood," or the river discharge with a recurrence interval of 1000 years). However, in light of increasing rainfall (IPCC 2001) , and more importantly, increasing rainfall intensity in the upper Midwest (Trenberth et al. 2003), the question becomes "how will possible climate-change factors influence flood frequency of the Upper Iowa River in Decorah, Iowa?"

The determination of flood frequency discharge for streams and rivers has received significant attention due to the prospects of more intense rainfall events (Trenberth et al. 2003) as a result of atmospheric warming by increased concentration of greenhouse gasses such as carbon dioxide. The use of continuous simulation for estimating flood frequency has been used in previous studies (Cameron et al. 2000, Cameron et al. 1999) wherein a stochastic rainstorm generator provided rainfall input for a TOPMODEL framework to determine rainfall runoff over 1000 years using simulated rainfall data. The stochastic rainfall model parameters were determined using observed rainfall data for several watersheds in the United Kingdom. Random rainstorms were generated by a Monte Carlo sampling procedure. As for the rainfall runoff, the Generalized Likelihood Uncertainty Estimation (GLUE) framework (Beven and Binley 1992) was employed to assess the uncertainty of using the hydrological model. An important defining feature of the GLUE framework is the rejection of the notion of a single, global optimum parameter set exists for the hydrological model. Rather, multiple parameter sets yielding behavioral results are employed to establish a 90% confidence interval for the projected flows.

In the current study, a Neyman-Scott rectangular pulse (NSRP) model is employed to generate simulated rainfall for the small (1395 km^2) Upper Iowa River watershed. The NSRP model parameters are determined through a sequence of fitting procedures on data collected from a recording rain gauge network distributed within the Upper Iowa watershed upstream from Decorah, Iowa. Parameter sets are determined for each month to allow for non-stationary characteristics in the rainfall climate. After the NSRP model parameters are determined, the model is used to generate rainfall data for a convective portion (primarily the months of June, July, August, and September) for each month and year of a 100-year period. The simulated rainfall data is used as input to a "blocked" (Nawarathna 2001) version of TOPMODEL, one in which the TOPMODEL framework is applied to each sub-watershed making up a partition of the whole watershed.

The annual peak flows determined over the 100 years of simulation are used in a log Pearson Type III distribution to determine discharges with 0.01-, 0.002-, and 0.001-annual exceedance probabilities. Projections based on the NSRP data are compared to projections made using the log Pearson Type III distribution technique on observed annual peak flow data recorded at an Upper Iowa River USGS gauging station in Decorah.

One of the primary objectives for developing a rainfall model is to study the effect climate variation may have on the discharges with 0.01-, 0.002-, and 0.001-annual exceedance probabilities. The NSRP model has seven parameters that are determined using the data collected on the Upper Iowa River rain gauge network. The model with this parameter set represents the "current" climate regime. Adjusting parameters, such as those that determine cell rainfall intensity and storm frequency, allow the NSRP model, with the adjusted parameter set, to simulate

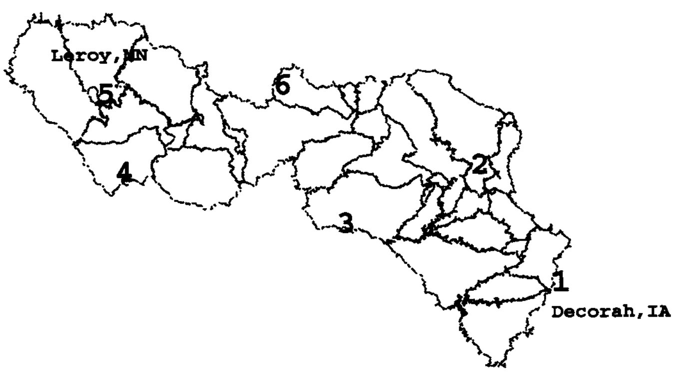


Fig. 1. Upper Iowa River watershed upstream from Decorah. Rain gauge locations are indicated by the numbers 1-6. Sub-watershed boundaries are depicted as well.

rainfall under a "new" climate regime. The rainfall data under the new climate is used as input to the blocked TOPMODEL framework so that peak annual discharges may be used with the log Pearson Type III distribution to project discharge probabilities under the new climate and compare with those determined for the current climate regime.

METHODS

Neyman-Scott Rectangular Pulse Rainfall Model

Arrival times for precipitation events (or storms) within the target watershed are determined using a Poisson distribution (parameter λ^{-1} = mean time [h] between storms). An individual storm consists of a cluster of cells. Constant rainfall intensity is assumed for each cell over its lifetime, creating a "rectangular pulse" of rainfall for the region covered by the circular cell. The intensity of a given cell is determined by an independent Weibull variable (parameters α = power parameter and θ = scale parameter [mm h^{-1}]). An independent exponential random variable determines the lifetime of a cell (parameter η^{-1} = mean lifetime [h] of a cell). Another independent exponential random variable gives the cell radius (parameter φ^{-1} = mean cell radius [km]). The spatial distribution for cells in the storm cluster is determined by a two-dimensional Poisson process (parameters μ = mean number of cells per storm, and ψ^{-1} = mean number of cells per unit area). The time lag between the storm origin and a given cell origin within the cluster is determined by an independent exponential random variable (parameter β^{-1} = mean time [h] between storm origin and cell starting times).

The e parameters of the NSRP model are determined using statistics based on observational spatial-temporal rainfall data collected from a recording rain gauge network (Fig. 1) within the Upper Iowa watershed. The assumption of the gauges being within a statistically homogeneous rainfall region appears to be reasonable based on an ANOVA F-test on the ptopottion of dty days (Table 1) for each site. The resulting p-value is 0.9852. Table 2 gives the values fot each parameter for each month.

Table 1. Gauge site coordinates (NAD27) and the proportion of dry days.

Site #	x-Coordinate (km)	y-Coordinate (km)	Mean Proportion of Dry Days
1	597.673	4795.427	.7123
2	588.368	4810.879	.7078
3	570.783	4802.240	.7278
4	541.829	4810.113	.7140
5	539.345	4820.501	.7170
6	562.571	4821.529	.7235

NSRP Simulated Rainfall

Once parameter estimates were calculated for each month through a series of fitting procedures, code was written in *R* (The R Project in Statistical Computing, 2010) to generate storm sets for June through September for each year of a 100-year period. For a given year and a given month, the process begins by determining storm arrival times based on the Poisson distribution. Next, a data set for each storm is generated using the appropriate random variables. The data set for storm i consists of n individual sets of data

$$\{\{(U_{i1},V_{i1}),S_{i1},L_{i1},X_{i1},R_{i1}\}\ldots\{(U_{ij},V_{ij}),S_{ij},L_{ij},X_{ij},R_{ij}\}\}\ldots$$
$$\{(U_{in},V_{in}),S_{in},L_{in},X_{in},R_{in}\}\}$$

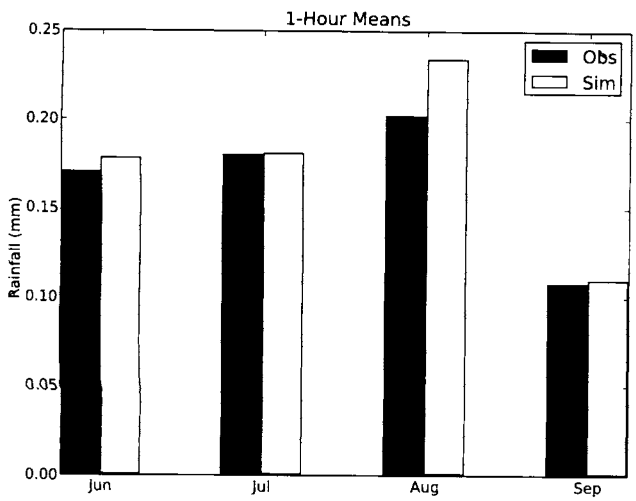
where the subscript j ($j=1, \ldots, n$) identifies the j^{th} cell in storm i. The ordered pair (U_{ij}, V_{ij}) specifies the cell center, S_{ij} determines the lag time between the storm starting time and the cell starting time, L_{ij} gives the cell's lifetime, X_{ij} is the cell's intensity, and R_{ij} specifies the cell's radius.

For a given month, the observed site data, recorded in years 2003–2008, for all gauges were lumped to determine dimensionless statistics. These statistics are: average intensity i_{ave}, variance σ^2, coefficient of variation η_{il}, autocorrelation ρ_{il}, skewness κ_{il}, and cross correlation $\rho_{i(j,k)}$. Index i corresponds to month number (i=6 for June, etc.), and index l specifies the amount of lag. Lag times of l = 1 hour and l=24 hours are used. The ordered pair (j,k) in the cross correlation subscript denotes the gauge site numbers used in the statistic.

A FORTRAN procedure uses the storm and cell data for a given season to determine the rainfall time series in 1-hour and 24-hourly intervals for each of the six gauge locations.

Table 2. Monthly parameter estimates.

Month	λ_i (h^{-1})	μ_{Ci} (#cells storm^{-1})	β_i (h^{-1})	η_i (h^{-1})	α_i (mm h^{-1})	φ_i (km^{-1})
June	0.0109	6.37	0.176	7.10	0.92	0.198
July	0.0053	7.58	0.198	4.98	1.09	0.500
August	0.0066	9.70	0.122	2.95	1.12	0.021
September	0.0043	6.90	0.011	1.56	0.98	0.086



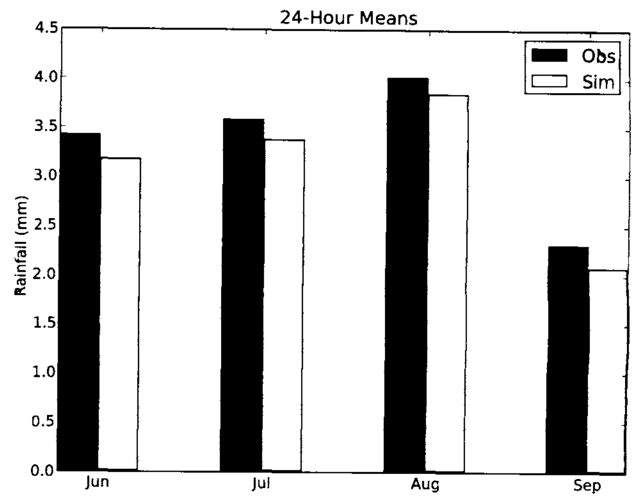


Fig. 2. Mean rainfall (mm) for 1-hour and 24-hour intervals from observed rain gauge data (obs) and simulated data (sim) generated by the NSRP rainfall model.

Comparisons between the simulated data statistics and the observed data statistics are done to determine the validity of the simulated rain data. Fig. 2 compares observed and simulated mean rainfall, in 1-hour and 24-hour intervals, for the months of June through August. Table 3 gives the values of each statistic for each month for both the observed data and the simulated data.

The two-sample Kolmogorov-Smirnov Test was conducted pairing observed gauge data against simulated gauge data on an hourly rainfall basis for each gauge and each month. The results are outlined in Table 4. With the exception of gauge 2 of July, there is insufficient evidence to reject, at the 95% confidence level, the null hypothesis that the two samples are drawn from the same distribution.

Another means of establishing the validity of the simulated rainfall data is to compare the inter-annual variability of the observed and simulated rainfall data. Daily rainfall recording began in 1893 for the city of Decorah. These data provide an independent data set because they were not used in the calculation of the NSRP model parameters. Values of monthly mean and variance for observed versus simulated data are summarized in Table 5. Simulated data show higher monthly averages for July and August. Larger discrepancies between simulated an observed data appear in the standard deviations. Except for July, observed monthly rainfall data exhibits greater variability than the simulated data.

River Discharge by TOPMODEL

The simulated rainfall data generated by the NSRP model was used as input for rainfall-runoff simulation of the Upper Iowa River watershed. The rainfall-runoff framework used is that of TOPMODEL (TOPography based hydrological MODEL) first published by Beven and Kirkby (1979). Beven et al. (1995) provide a review of the history of TOPMODEL and its various applications.

Methods that treat the entire watershed as a single entity are referred to as "lumped" models. Alternatively, fully distributed models make water storage and flow calculations on each watershed element. The use of hydrological characteristics, such as element slope and drainage area, to establish hydrological similarity groups represents a compromise "semi-distributed" approach.

TOPMODEL uses digital elevation model (DEM) data to determine a hydrological index for each element defined by the DEM grid. In this study, watershed elements measure 30 meters on an edge. The hydrologic index for a given element is the area within the watershed that drains through the element divided by the slope of the element. A low-elevation element with shallow slope would give a high index, while a steep-sloped element at a higher elevation would have a low index. All elements within the watershed having the same hydrological index are assumed to respond in a similar hydrological way to rainfall events.

Equations used in TOPMODEL are based on the continuity equation and Darcy's Law. The resulting mathematical model is simplified under the assumption that the hydraulic gradient of subsurface flow is equal to the land-surface slope. Additionally, it is assumed that the redistribution of water within the subsurface can be approximated by a series of consecutive steady states. These assumptions are valid for primarily wet catchments that have shallow, homogeneous soils.

Table 3. Observed (Obs.) and simulated (Sim.) rainfall statistics. The coefficient of variance ($\mathbf{v}_1$), autocorrelation ($\boldsymbol{\rho}_1$), skewness ($\boldsymbol{\kappa}_1$) for 1-hour data, and the coefficient of variance ($\mathbf{v}_{24}$) and autocorrelation ($\boldsymbol{\rho}_{24}$) for 24-hour data.

	$\mathbf{v}_1$		$\boldsymbol{\rho}_1$		$\boldsymbol{\kappa}_1$		$\mathbf{v}_{24}$		$\boldsymbol{\rho}_{24}$	
Month	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.
June	7.31	6.96	0.289	0.203	14.2	13.4	2.29	2.13	−0.0025	0.0675
July	10.2	10.3	0.329	0.238	20.5	21.6	3.27	3.25	0.0019	0.0760
August	7.52	7.04	0.321	0.343	14.0	12.9	2.39	2.25	0.1570	0.0954
September	8.14	7.76	0.446	0.393	14.1	13.9	3.07	2.34	0.2120	0.1900

Table 4. Results of the two-sample Kolmogorov-Smirnov test.

Month	June	July	August	September
Gauge 1				
D-statistic	.0122	0.147	.011	.0031
p-value	.8058	.5697	.8814	1
Conclusion	Fail to reject	Fail to reject	Fail to reject	Fail to reject
Gauge 2				
D-statistic	.0223	.0271	.01	.0036
p-value	.1258	.0303	.9384	1
Conclusion	Fail to reject	Reject	Fail to reject	Fail to reject
Gauge 3				
D-statistic	.0096	.085	.009	.0051
p-value	.962	.986	.974	1
Conclusion	Fail to reject	Fail to reject	Fail to reject	Fail to reject
Gauge 4				
D-statistic	.0095	.0056	.0131	.0105
p-value	.9626	1	.7095	.9202
Conclusion	Fail to reject	Fail to reject	Fail to reject	Fail to reject
Gauge 5				
D-statistic	.0077	.0104	.017	.0104
p-value	.9968	.9184	.3817	.9247
Conclusion	Fail to reject	Fail to reject	Fail to reject	Fail to reject
Gauge 6				
D-statistic	.0157	.0049	.0096	.0092
p-value	.498	1	.9563	.9733
Conclusion	Fail to reject	Fail to reject	Fail to reject	Fail to reject

Spatial variability in a larger watershed may be captured by partitioning the river's large catchment into smaller sub-watersheds on the basis of drainage areas for tributaries and streams that feed the river. TOPMODEL principles applied to each individual sub-watershed leads to a "block-wise" application. This approach has been used by Nawarathna, et al. (2001) in modeling large watersheds. Such an approach is used in this study. The watershed is partitioned into 31 sub-watersheds as shown in Fig. 1.

An extremely important aspect of any model is the measurement or assignment of model parameters. Values for seven parameters must be specified in the TOPMODEL framework. They are the transmissivity of saturated soil, effective depth of soil profile (exponent in saturated subsurface flow rate), maximum root zone storage capacity, time constant for vertical flux through the unsaturated zone, sub-watershed internal routing velocity, surface hydraulic conductivity, wetting front suction, and water content change across the wetting front (only if infiltration excess calculations are used), and main channel routing velocity. The uncertainty in the model's parameter values may require many thousands of trial runs in order to establish some interval of confidence for model results. The efficiency offered by a semi-distributed framework such as TOPMODEL is significant.

Table 5. Comparison of observed and simulated rainfall data for Decorah, Iowa.

	Statistic			
	Mean (mm)		Standard Deviation (mm)	
Month	Observed	Simulated	Observed	Simulated
June	113.9	99.8	158.9	78.9
July	104.1	116.8	137.9	247.6
August	101.3	106.1	171.7	114.6
September	92.2	61.5	119.6	71.1

For a given run of TOPMODEL using observed rainfall data, parameter sets for each of the 31 sub-watersheds were created using a Monte Carlo method. A value for each parameter was randomly selected from an interval of likely values. A set of parameter values was deemed "behavioral" if the Nash-Sutcliff goodness-of-fit measure is greater than a specified threshold. The Nash-Sutcliff measure is calculated comparing simulated river discharge to observed discharge. Because annual peak flow is of primary interest in this study, the Nash-Sutcliff calculation is determined over time intervals (roughly four to six days) corresponding to annual peak flows in the observed discharge record for years 2004 through 2008. This approach is similar to that employed by Cameron et al. (2000).

For each of the one-hundred years of simulated data, using the behavioral parameter sets as described above, an annual maximum discharge was determined for the Decorah gauging station location. Fig. 3 shows a scatter plot of the annual maximum discharge for each of the 100 years. Note that the maximum discharge for the 100-year simulation is 637 m^3s^{-1}, approximately 9% less than the 702 m^3s^{-1} 1%-annual event projected by Eash (2001) using 83 years of observed maximum annual discharge and a Pearson Type III distribution.

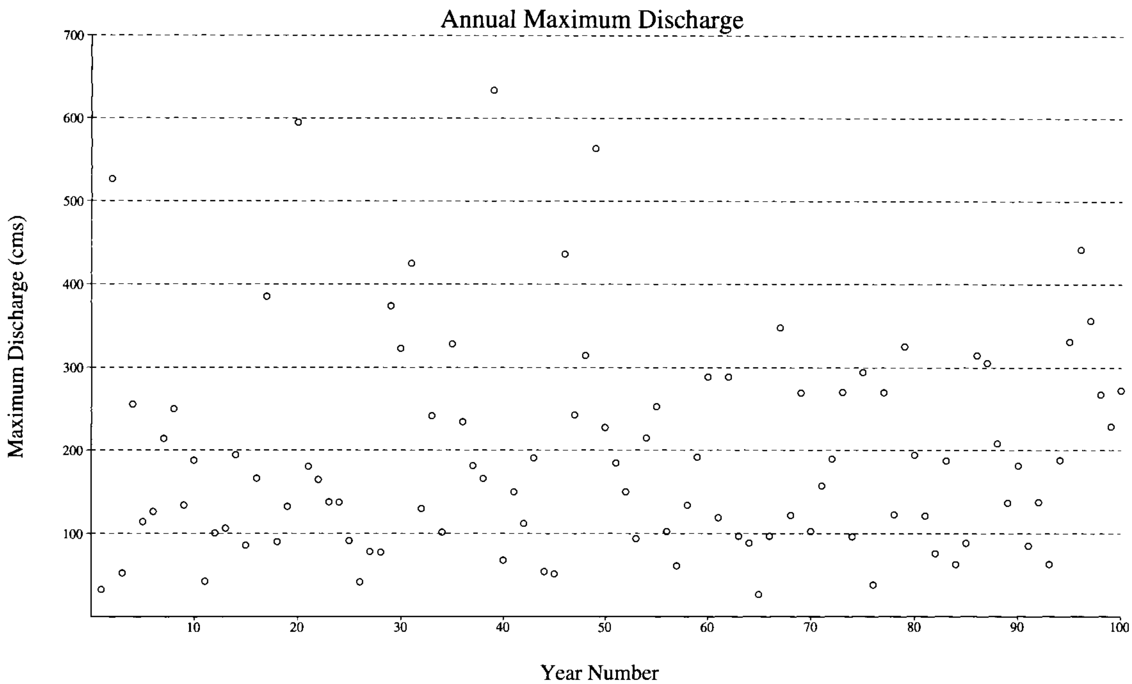


Fig. 3. **Upper Iowa River annual maximum discharge ($m^3\ s^{-1}$) using NSRP simulated rainfall data.**

Pearson Type III Distribution

Flood-frequency is analyzed by fitting a Pearson Type III distribution to the logarithms (base 10) of the annual peak discharges (Interagency Advisory Committee on Water Data 1981). The formula for discharge Q is

$$\log Q = q_{ave} + Ks,$$

where q_{ave} is the average of the logarithm of observed annual peak discharges, s is a skew coefficient, and K is a parameter based on the skew and exceedance probability. The appropriate skew coefficient was determined by adjusting a generalized regional skew coefficient, determined from a map published by the Interagency Advisory Committee on Water Data (1981), for regional bias. The adjustment is given by

$$s = Ws_s + (1\text{-}W)S_r$$

where s_s is the station skew, s_r is the regional skew coefficient, and the weighting factor W is given by

$$W = V(s_r)/(V(S_r) + V(S_s)),$$

where $V(s_r)$ or $V(s_s)$ is the variance of the respective quantity. The variance of the region skew is determined from a map (Interagency Advisory Committee on Water Data 1981). The station skew was determined from Eash (2001), and the station skew variance was obtained from the results of Monte Carlo experiments by Wallis et al. (1974). Values for K are determined once the adjusted skew coefficient is known (Interagency Advisory Committee on Water Data 1981). The actual K value depends on the exceedance probability as well.

Climate Change Sensitivity

The water-holding capacity of the atmosphere, determined by the Clausius-Clapeyron equation, increases by 7% per one degree Kelvin increase in atmospheric temperature. Indeed, precipitable water below the 500 hectopascal level has increased by approximately 5% per decade in the western hemisphere north of the equator (Ross and Elliot 1995). Trenberth et al. (2003) conclude that, because heavy rainfall rates greatly exceed evaporation rates, these events depend on low-level moisture convergence so that rainfall intensity should increase at roughly the same rate (7% K^{-1}) as atmospheric moisture. The Intergovernmental Panel on Climate Change (IPCC) models predict an overall increase in total precipitation of 1–2% K^{-1} (IPCC 2001). The 7% increase in rainfall intensity would be at odds with the 1–2% increase in overall rainfall unless the distribution of event intensities evolves in such a way that fewer light to moderate events occur in favor of more intense events. Alternatively, a decrease in the frequency of events may occur, as found by Hennessey et al. (1997), to give an overall 1–2% rainfall increase. The net 1–2% increase in rainfall would be balanced by a similar increase in evapotranspiration (Trenberth et al. 2003).

RESULTS AND DISCUSSION

Table 6 provides a comparison of results based on 100 years of simulated data to those determined using observed annual peak flow data measured at the USGS recording station in Decorah. Quantities shown are for annual exceedance probabilities of 0.01, 0.002, and 0.001. An annual exceedance probability of 0.01 corresponds to the so-called "100-year flood," 0.002 corresponds to the 500-year flood, and 0.001 corresponds to the 1000-year flood. Flow projections based on observation are given in the column labeled "USGS."

Table 6. Flood frequency comparison: USGS calculations versus NSRP rainfall model results. Discharge quantities are m^3s^{-1}.

Annual Exceedance Probability	Trial						
	USGS	NSRP-current climate			NSRP-new climate		
		5%	Median	95%	5%	Median	95%
0.010	606	263	442	716	441	532	1039
0.002	702	408	628	932	767	968	1410
0.001	736	481	719	1025	951	1118	1477

Current Climate

NSRP results for the "current climate," shown in the second column of Table 6, are determined using TOPMODEL and the generalized likelihood uncertainty estimate (GLUE) framework (Bevin and Brinley 1992). The flows are determined using 1000 per-selected parameter sets deemed behavioral using the Nash-Sutcliffe goodness of fit calculation on simulated discharge values versus observed values associated with flow peaks in the observed records for years 2004 through 2008, similar to methods employed by Cameron et al. (2000). For a given year, the annual peak flow for each of the 1000 parameter sets is calculated. These flows are ranked largest to smallest. Flows at the 95^{th}, 50th, and 5^{th} percentiles are identified from the ranking.

As with the observed annual maximum flow data, the annual peak flows determined over the 100 years of simulated rainfall are used in a log Pearson Type III distribution to determine discharges with 0.01, 0.002, and 0.001 annual exceedance probabilities for each of the three percentiles (95^{th}, 50^{th}, and 5^{th}). These results are shown in Table 6. The 95^{th} and 5^{th} percentiles establish a 90% confidence interval. It is noted that the projections in column one using USGS data fit well within the 90% confidence interval shown in the NSRP-current climate columns.

New Climate

Changes to the NSRP rainfall generation model were made to simulate the second likely scenario outlined in the previous paragraph. That is, the average rainfall intensity is increased by 7% and the event frequency is decreased so that a net annual rainfall increase of 2% is realized. The "new climate" columns of Table 6 summarize the discharge results for the new climate regime. The median flow of 532 m^3 s^{-1} for the 0.01 annual exceedance probability under the new climate regime represents, approximately, a 20% increase over the same statistic under the current climate regime. For the 0.002 and 0.001 probabilities, the percentage increases are approximately 55%. The results suggest a much stronger amplification for the more extreme events.

It is interesting to consider the change in the probability of exceedance of the 100-, 500-, and 1000-year flow quantities of the current climate in the new climate. This may be done by inverting the log-Pearson III method for finding discharge values from exceedance probabilities. The relationship is invertible, but the accuracy of the inversion is compromised because of the need to interpolate coarse tabular spacing on probability values. The flow volume of 442 m^3s^{-1} has an annual probability of exceedance of 0.01 in the current climate. This volume flow in the new climate regime has annual probability of exceedance between 0.05 and 0.1. That is, the discharge in the currenr climate that has a 100-year recurrence interval will have a recurrence interval between 10 and 20 years. The flow of 702 m^3s^{-1} in the current climate has an annual probability of exceedance of 0.002, resulting in a recurrence interval of 500 years. In the new climate, the recurrence interval for this discharge is approximately 50 years. Finally, the discharge of 736 m^3s^1 has a probability of exceedance of 0.001 in the current climate, resulting in a recurrence interval of 1000 years. In the new climate, this flow has a recurrence interval between 50 and 100 years.

Conclusions

The NSRP model is a useful component in projecting rainfall-runoff in catchments similar to the Upper Iowa River. This conclusion is based on the following: 1) similarity in statistics, such as monthly means, coefficient of variance, and autocorrelation for one- and twenty four-hour intervals, in modeled and observed rainfall 2) the two-sample Kolmogorov-Smirnov test used on model and observational rainfall data indicate that the samples are drawn from the same distribution, and 3) the projected 100- and 500-year discharges for the Upper Iowa River determined using NSRP model data, the TOPMODEL rainfall-runoff methodologies, and the GLUE framework are consistent with those found by observation.

This positive conclusion is made with the knowledge that the cross-correlation statistic is one weakness in the simulated data. It is noted that previous work done using a similar NSRP (Cowpertwait 2002) model makes little or no reference to the same statistic. Perhaps this is systemic problem in the model. It is also noted that the observed rainfall data record is a relatively short period of four years, which limits the confidence in the results as well.

Further, the five-year length of the observed rainfall data segment is relatively short, so it may not provide an accurate sample of the current climate regime. Likely, the smaller inter-annual variability of monthly means, as shown in Table 5, are attributable to the short length of the observed data collected on the Upper Iowa River gauge network. As more years of data are added to the record and incorporated in the parameter fitting process, the resulting NSRP model rainfall will more confidently represent the rainfall climate for the Upper Iowa watershed.

The confidence intervals shown for the simulated outflow data in Table 6 are relatively large in some instances. These intervals could, perhaps, be narrowed by studying the variance in the peak discharge data as a function of the variance in parameter values.

The primary methodologies in this study are the stochastic NSRP rainfall model, the semi-distributed TOPMODEL rainfall runoff framework, and the log Pearson Type III distribution for determining flow rates corresponding to certain annual occurrence probabilities. Each may be used together or independently in other watersheds with the following provisions. In the case of the NSRP rainfall model, a sufficient number of seasons of hourly data from a recording rain gauge network that spans the watershed. The TOPMODEL framework requires a digital evaluation model for the watershed, as well as a sufficient time series of stream discharge. The Pearson Type III probability distribution method can be applied to any watershed provided the regional and station skew coefficients are known.

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LITERATURE CITED

BEVEN, K. and M. J. KIRKBY. 1979. A physically based variable contributing area model of basin hydrology. Hydrological Sciences Bulletin 24:43–69.

BEVEN, K. J. and A. M. BINLEY. 1992. The future of distributed models: Model calibration and uncertainty prediction. Hydrological Processes, 6:279–298.

BEVIN, K. J., P. QUINN, R. ROMANOWSKI, and J. FREER. 1995. Pages 627–668. *In*: Computer models of watershed hydrology. Water Resource Publications, Colorado.

CAMERON, D., K. BEVEN, J. TAWN, and P. NADEN. 2000. Flood frequency estimation by continuous simulation (with likelihood based uncertainty estimation). Hydrology and Earth Systems Sciences 4(1): 23–34.

CAMERON, D., K. BEVINS, J. TAWN, S. BLAKOVA, and P. NADEN. 1999. Flood frequency estimation for a gauged upland catchment (with uncertainty). Journal of Hydrology 219:169–187.

COWPERTWAIT, P. S. P., C. G. KILSBY, and P. E. O'CONNELL. 2002. A Space-time Neyman-Scott model of rainfall: Empirical analysis of extremes. Water Resources Research 38(8): 1–14.

EASH, D. A. 2001. Techniques for estimating flood-frequency discharges for streams in Iowa: United States Geological Survey Water Resources Report 00-4233. United States Geological Survey, Iowa City, Iowa.

HENNESSEY, K. J., J. M. GREGORY, and J. F. B. MITCHELL. 1997. Changes in daily precipitation under enhanced greenhouse conditions. Climate Dynamics 13:667–680.

IPCC. 2001. Climate change 2001: The scientific basis. Houghton, et al., Eds. Cambridge University Press, Cambridge, United Kingdom.

INTERAGENCY ADVISORY COMMITTEE ON WATER DATA. 1981. Flood flow frequency. Bulletin #17B of the hydrology subcommittee. United States Office of the Interior. Reston, Virginia.

NAWARATHNA, NMNSB., T. Q. AO, S. KAZAMA, M. SAWAMOTO, and K. TAKEUCHI. 2001. Influences of human activities on the BTOPMC model Runoff simulations in large-scale watersheds., Pages 93–99. *In* XXIX LAHR Congress Proceedings, Theme a.

The R Project for Statistical Computing. 2010. Release 2.11.1.

ROSS, R. J. and W. P. ELLIOT. 1996. Tropospheric water vapor climatology and trends over North America: 1973–93. Journal of Climate 9:3561–3574.

TRENBERT, K. E., A. DAI, R. M. RASMUSSEN, and D. B. PARSONS. 2003. The changing character of precipitation. Bulletin of the American Meteorological Society 84(4): 1205–1217.

WALLIS, J. R., M. C. MATALAS, and J. R. SLACK. 1974. Just a moment. Water Resources Research 10(2): 211–219.