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Stream hydrological and ecological responses to climate change assessed with an artificial neural network

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Abstract

An artificial neural network (ANN) was used to evaluate the hydrological responses of two streams in the northeastern U.S. having different hydroclimatologies (rainfall and snow+rain) to hypothetical changes in precipitation and thermal regimes associated with climate change. For each stream, historic precipitation and temperature data were used as input to an ANN, which generated a synthetic daily hydrograph with high goodness-of-fit ($r^2 > 0.80$). Four scenarios of climate change were used to evaluate stream responses to climate change: +25% precipitation, −25% precipitation, 2× the coefficient of variation in precipitation regime, and +3°C average temperature. Responses were expressed in hydrological terms of ecological relevance, including flow variability, baseflow conditions, and frequency and predictability of floods. Increased average precipitation induced elevated runoff and more frequent high flow events, while decreased precipitation had the opposite effect. Elevated temperature reduced average runoff. Doubled precipitation variability had a large effect on many variables, including average runoff, variability of flow, flooding frequency, and baseflow stability. In general, the rainfall-dominated stream exhibited greater relative response to climate change scenarios than did the snowmelt stream.

Stream ecosystems are at risk for changes due to climate change because ecological processes are strongly influenced by seasonal patterns of precipitation, runoff, and temperature (Carpenter et al. 1992; Allan 1995). If historical hydrological and thermal regimes in streams are modified by anthropogenically altered climate change, then ecosystem alteration is to be expected. Hydrological modifications may result either from changes in average conditions or from changes in the distribution and timing of extreme events such as floods and droughts. Evaluating the extent to which stream hydrographs are modified by scenarios of climate change can provide important information on the relative sensitivity of stream ecosystems to potential climate change.

Modeling stream hydrological response to climate variation can be performed with a variety of techniques. If detailed watershed and climate data are available for parameterization, one can use mass balance models, such as hydrological budget models (e.g. Gleick 1987). However, for many stream systems, detailed watershed data are lacking, making the mechanistic modeling of hydrological response to climate difficult. Further, traditional empirical models (e.g. regression models) may not perform well due to structural constraints (e.g. linearity) and paucity of data. Neural network analysis is a recently developed modeling technique that may be useful in simulating hydrological response to climate change in basins with limited data. We used this technique in examining the hydrographic response of streams in Maryland and New York to various scenarios of climate change. The responses of several hydrological variables were examined, such as measures of flow variability, and timing and frequency of low and high flow extremes. That such hydrological descriptors can influence ecological processes and patterns in stream ecosystems has received attention (*see* Minshall 1988; Poff and Ward 1989, 1990) and some limited empirical support (e.g. Horwitz 1978; Poff and Allan 1995).

Materials and methods

Study streams—Two streams in the northeastern U.S. were chosen based on the availability of long-term daily discharge data from the U.S. Geological Survey and on differing hydroclimatology. The Little Patuxent River is near Baltimore, Maryland. It has a basin area of 97 km^2 and an average annual discharge of 1.41 $m^3 s^{-1}$, A U.S. Geological Survey water stage recorder was installed at the site (gauge 01593500) and daily discharge data are available since 1932. Considerable development occurred in the basin before the 1970s; therefore, we limited our historical record to the 21-yr period of 1972–1992. Runoff in this stream is dominated by rainfall because the stream is too far south to allow significant snowpack accumulation on an annual basis. Annual rainfall in the basin averages ~115 cm, and snowfall averages ~55 cm. The

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range in annual temperatures in the basin is -27 to 39°C, with an average of 7°C.

The Independence River is in upstate New York. The recorder gauge (04256000) is near Donnattsburg at an elevation of 297 m. On an annual basis, the 230-km^2 basin receives 117 cm of rainfall and 455 cm of snow and has a discharge of 6.05 m^3s^{-1}. The hydrology of this system is strongly influenced by the storage of precipitation as snow, as indicated by the strong seasonal peaks in streamflow (*see below*). The range in annual temperatures in this basin is -43 to 36°C, with an average of 5°C.

In the terminology of Poff and Ward (1989), the rainfall-dominated Little Patuxent River is a perennial runoff stream type characterized by high temporal variation in flow, and the Independence River is a snow plus rain (snow+rain) stream type, characterized by both late spring snowmelt peak flows and nonseasonal rainfall peak flows. In a recent analysis, Poff (1996) found perennial runoff streams to constitute 47% and snow+rain streams 12% of 816 gauged streams in the U.S. having relatively unimpaired flow. None of the other eight types of streams they identified comprised as large a fraction of the total sample size. These two stream types are representative of major stream types commonly found in the northeastern U.S. (Poff 1996); therefore, analyses of their responses to plausible scenarios of climate change in this region have general implications for many streams in the region.

Climate change scenarios—Four scenarios were specified to span a range of potential regional climate alterations in precipitation and thermal regimes. In scenario 1, average daily precipitation was increased 25% by increasing the daily precipitation input value for the model (*see below*) by a factor of 1.25. This scenario represents a worst-case scenario for increased precipitation for the region. In scenario 2, precipitation was decreased by 25% to represent a worst-case scenario of reduced precipitation for the region. In scenario 3, the coefficient of variation (C.V.) in daily precipitation was doubled (described below) to simulate an increase in climate variability. Increases in climate variability and storminess have been proposed to result from a heated, more energetic atmosphere (e.g. Rind et al. 1989). In scenario 4, the average temperature was increased by 3°C. Each daily temperature input to the model (*see below*) was simply increased by 3°C.

Hydrological variables—The hydrological regimes of both rivers were described with hydrological characteristics of presumed ecological importance. Hydrological characteristics were derived for each river from the observed historical records, from the simulated baseline records, and from each of the hypothetical climate change scenarios. The hydrological statistics derived fall into three categories: mean flow conditions, high flow extremes, and low flow extremes. The derivation and a thorough description of these variables is provided by Poff and Ward (1989) and Poff (1996). Mean flow conditions were described by three variables. The *mean daily discharge* (m^3s^{-1}) is simply the average flow in the channel. The *C.V. of daily flow* (%) is the standard deviation divided by the mean times 100. The *predictability of daily flow* (%) is a formal measure of predictability based as described by Colwell (1974) and ranges from 0 to 100. High flow extremes were summarized by three variables. *Flood frequency* (yr^{-1}) is the average number of annual bankfull events having a recurrence probability of 1.67 yr based on a lognormal distribution. *Flood predictability* is the extent to which all bankfull events occurring over the entire period of record fall into a 60-d period (an arbitrary characterization of season). Flood predictability ranges in value from 0.167 (uniform distribution of floods over six seasons) to 1.0 (all floods in a given season). The *flood-free period* is the maximum fraction of year during which no bankfull events have ever occurred over the period of record; it represents the length of the nonflooding season. Low-flow extremes were described by the *baseflow index,* which is the average across all years of the annual minimum flow to mean flow. This value indicates the extent to which the stream drops below the average condition toward intermittency. For each stream, these variables were derived from the 21-yr historical hydrograph (1972–1992), from a simulated 21-yr hydrograph using historical precipitation and temperature data and from a 21-yr simulated hydrograph for each of the four climate change scenarios. The simulated historical hydrograph was used as a baseline against which simulated hydrologic changes associated with climate change could be assessed.

In the modeling process, we had to decide whether to try to capture high-flow vs. low-flow extremes. We were primarily interested in capturing the most dynamic component of the hydrograph, (i.e. the short-duration high-flow extremes that can often be resolved only with a daily time step). Therefore, the models were optimized so that they would track the high-flow extremes preferentially over the low-flow extremes.

Artificial neural network (ANN) model—ANN design is inspired by current understanding of the mammalian brain structure and nervous system. The ANN is believed to provide better solutions than traditional methods when applied to complex systems that may be poorly defined and understood, problems that deal with noise or involve pattern recognition, and situations where input data are incomplete or ambiguous by nature.

An ANN structure is composed of two main units: a processing element that is analogous to a neuron and interconnections (or weights) between these elements that imitate the synaptic strength in a biological nervous system. As in the biological nervous system, an artificial neuron receives signals from other neurons or outside through synaptic connections (Wasserman 1989). The neuron processes this information and if the synaptic strength of the input exceeds a certain threshold, an output signal is sent to other neurons in the networks.

In an ANN architecture, the neurons are arranged in groups called layers. As illustrated in Fig. 1, the basic architecture of an ANN usually consists of three layers: an input layer where the incoming information is presented to the network; a hidden layer where the learning takes place; and an output layer which generates network output(s) (Hect-Nielsen 1990).

The most distinctive characteristic of an ANN is its ability to learn from examples. Learning is defined as self-adjustment of the network weights as a response to changes in its information environment. When a set of inputs is presented, a network adjusts weights in order to approximate the target output based on predefined rules and procedures. Learning or training in ANNs consists of three elements: weights between the neurons that define the relative importance of the inputs, a transfer function that controls the generation of the output from a neuron, and learning laws that describe adjustment of the weights during training according to an algorithm (Caudill 1987). During learning a neuron receives inputs from the input (or previous) layer, weights each input with a preassigned value, and combines these weighted inputs. The combination of the weighted inputs is represented as

$$\text{net}_j = \Sigma w_{ij} x_i.$$

net_j is the summed weighted input for jth neuron, w_{ij} is the weight from ith neuron in the previous layer to the jth neuron at the current layer, and x_i is the input from the ith to the jth neuron. The net is either compared to a threshold or passed through an transfer function to determine the level of activation. If the activation of a neuron is strong enough, it produces an output that is sent as input to other neurons in the next layer. The most commonly used continuous transfer functions are sigmoidal and hyperbolic tangent (tanh) functions. In this study, tanh function was used as a transfer function.

In supervised learning, a pair of input-output data, called the training pair, is introduced to a network. The network computes the outputs for a given set of inputs and compares these outputs with the target. The goal is to find the vector of weights that minimizes the mean-squared error between the computed and target outputs according to

$$F(w) = \min \Sigma(y_i - y_i^*)^2.$$

$F(w)$ is the objective function, and y_i^* and y_i are the computed and target outputs. The difference between computed and target outputs is used to modify the weights in a network by minimizing the error term $(y_i - y_i^*)$ using a gradient search method, such as steepest descent, and a learning law, such as the generalized delta rule (*see* Tokar 1995).

In the development of the rainfall-runoff model used in this study, we selected a back-propagation network with one hidden layer. Recorded values of average daily precipitation (as rain or snow) and temperature for the stream basin were used to estimate daily discharge values. Where snowfall accumulation was significant, a snow-water equivalent and a melting algorithm were used (Tokar 1995). Two separate data sets for each stream were formed from the historical data to train and test the prediction ability of the network. For the Little Patuxent River, training was performed with data for 1979, 1980, and 1984, which represent years of high flow, low flow, and average flow. Similarly, high, low, and average flow years were used to train the model for the Independence River with data from 1976, 1982, and 1975. For each stream the best-trained model was determined based on the minimization of sum-of-squared distances between the observed and predicted runoff values (*see* Tokar 1995). The trained models were then tested with data for 1989, 1991, and 1992 for the Little Patuxent River and 1978, 1990, and 1983 for the Independence River. The same statistical criterion was used to assess performance of the trained model. Training of the networks was accomplished with NeuralWorks Professional II/PLUS software developed by NeuralWare, Inc.

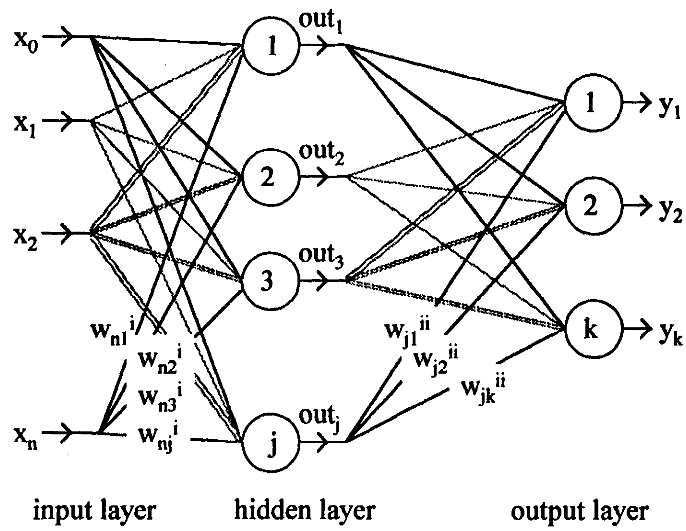

Fig. 1. Conceptual sketch of one-hidden-layer artificial neural network. x_n is the nth input to the network (e.g. precipitation, temperature, snowmelt), $w_{nj}{}^i$ is the weight of the nth input to the jth neuron in the ith layer, out_j is the output of the jth neuron in the hidden layer, $w_{jk}{}^{ii}$ is the weight of the input from the jth neuron in the hidden layer (out_j) to the kth neuron in the iith layer, and y_k is the kth output of the network (e.g. streamflow).

Simulations of rain and snowfall were achieved by frequency analysis using 21 yr of daily precipitation data and the Monte Carlo simulation technique as follows. Daily rain and snowfall values for 21 yr were used in the frequency analysis to select the probability distribution function with the aid of χ^2 goodness-of-fit test (McCuen 1993). Based on the frequency analysis, we selected a gamma distribution for the simulations of rain and snowfall. The gamma probability distribution function was used to generate synthetic rain and snowfall data (*see* Ang and Tang 1990). For scenario 3, the C.V. of this distribution was doubled. The synthetic rain and snowfall data resulting from this process were applied as input to the rainfall-runoff model and the discharge values for various scenarios were computed (Tokar 1995).

Results

Model training and verification—The ANN model tracked the hydrograph of the Little Patuxent River reasonably well for the 3-yr period, producing good agreement between the observed and predicted daily discharge

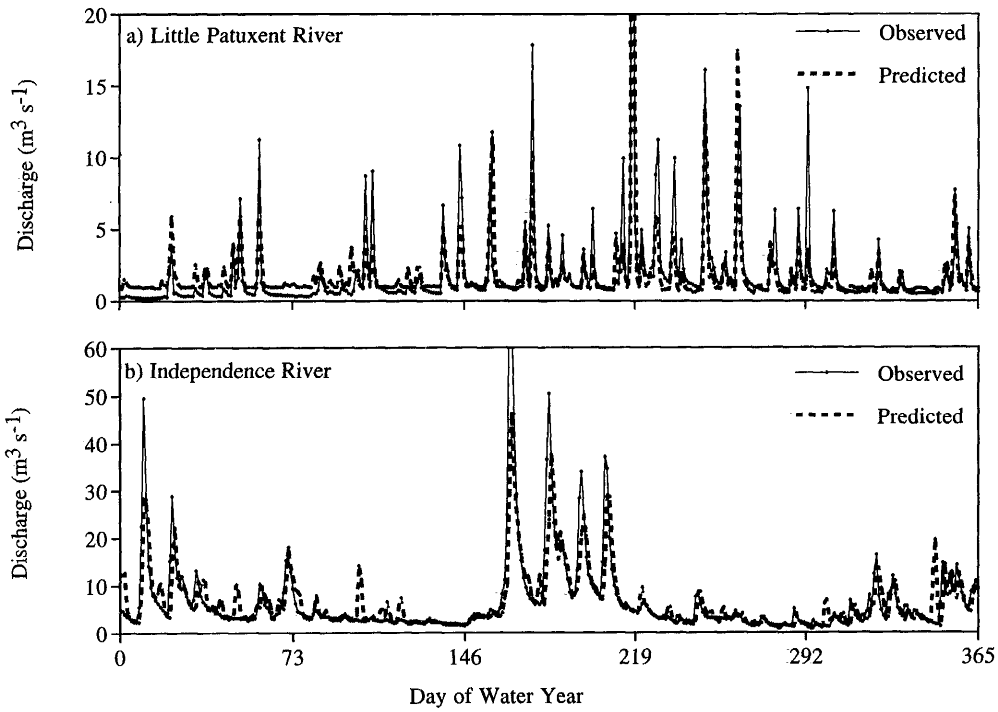

Fig. 2. Comparison of observed daily discharge vs. discharge simulated by the ANN model for a representative year for the Little Patuxent and Independence Rivers. Water year is 1 October–30 September.

values (r^2 = 0.80). The trained model was verified with precipitation and temperature data from a separate 3-yr period, which produced a high correlation between predicted and observed discharge values (r^2 = 0.83) (Fig. 2a). For the Independence River, model training for the 3-yr period resulted in good agreement between observed and predicted daily discharges (r^2 = 0.79). Testing of the trained ANN produced a similarly good fit (r^2 = 0.84) (Fig. 2b).

The ability of the ANN model to correctly simulate the various hydrological statistics is summarized in Table 1. For the Independence River, the simulated statistics compared favorably with the actual values calculated from the historical record, with the exception of flood frequency. For the Little Patuxent River, some simulated statistics showed greater deviation from actual values (e.g. average flow, predictability of daily flow, baseflow).

Table 1. Summary of historical (Hist.) and simulated (Model) hydrological conditions for the Little Patuxent and Independence Rivers.

	Little Patuxent		Independence	
Variable	Hist.	Model	Hist.	Model
Average flow (m^3 s^{-1})	1.41	1.64	6.05	6.07
Daily C.V. (%)	177	142	115	100
Predictability of daily flow (%)	44.4	64.0	48.9	46.8
Flood frequency (yr^{-1})	1.3	1.1	2.6	1.7
Flood predictability (fraction in season)	0.27	0.30	0.56	0.59
Flood-free period (fraction of year)	0.15	0.18	0.33	0.28
Baseflow (min/mean)	0.14	0.32	0.16	0.12

Hydrological responses to climate change scenarios—The responses of seven hydrological statistics (relative to the simulated historical hydrograph) to the four climate change scenarios for the two rivers are summarized in Fig. 3. The responses of various statistics differed depending both on the river and climate change scenario being simulated.

In scenario 1, precipitation was increased by 25%, which resulted in much greater hydrological responses in the Little Patuxent River compared to the Independence (Fig. 3a). In particular, flood frequency increased dramatically from 1.1 to 2.5 floods yr^{-1}, and the fraction of the year without flooding decreased from 18 to 7%. Mean flow and flow variability also increased somewhat. In the Independence River, the only statistic that increased markedly was annual flood frequency (from 1.7 to 2.0).

In scenario 2, precipitation was reduced by 25%, and the hydrological response of the Little Patuxent was again greater than that the Independence River (Fig. 3b). In the Little Patuxent, mean flow, variation in flow, and flood frequency declined, and seasonality of floods and baseflow stability increased. In the Independence River, the largest change was a 25% reduction in flood frequency coupled with a small increase in flood seasonality.

In scenario 3, the C.V. in daily precipitation was doubled, and this induced some very large hydrological changes in the two rivers (Fig. 3c). In the Little Patuxent, flood frequency dramatically increased (from 1.1 to 5.4), while there was a reduction of ~80% in the predictability of the flood-free period (from 18 to 4% of the year). Mean flow increased by ~50% and variation in flow more than doubled. In the Independence River, flood frequency increased by ~60% (from 1.7 to 2.7) and the length of the flood-free period was diminished from 28% of the year to 17%.

In scenario 4, an increase in average temperature of 3°C caused modest changes in hydrological characteristics in the two streams (Fig. 3d). In the Little Patuxent, flood frequency and baseflow stability declined by ~20%, and flood predictability increased by 30%. In the Independence River, similar but less dramatic trends were seen, with the exception that flood frequency increased slightly, as did measures of flood seasonality (Fig. 3d).

Discussion

Ecological implications—The literature on the specific ecological effects of hydrological regime on stream ecosystem structure and function is incomplete, largely because hydrological regime is an integrative descriptor of numerous selective forces and habitat conditions and cannot easily be viewed in isolation. Nonetheless, there is widespread appreciation that hydrological conditions, particularly extreme events, play a central role in stream ecology (e.g. Hynes 1970; Peckarsky 1983; Minshall 1988; Resh et al. 1988; Poff and Ward 1989; Townsend and Hildrew 1994; Allan 1995) and that climate change that alters these conditions has important implications for stream processes and patterns (Carpenter et al. 1992; Poff 1992; Grimm 1993). Characterizing streams by their historical hydrological regimes, as was done by Poff and Ward (1989), provides a baseline against which the impacts of climate change induced hydrological modifications can be evaluated. The basic premise of this approach is that the more a modified hydrological regime deviates from the historical norm, the greater the inferred ecological consequence (*see* Poff and Ward 1990).

In the present study, the hydrological responses of two important classes of stream types in the U.S. (perennial runoff and snow+rain streams) differed under four scenarios of climate change (Fig. 3). The primary differences in response have to do with the flood regime, and our discussion will focus on that hydrological component.

Floods have been shown to influence stream ecosystems in numerous ways, such as exporting resources (Bilby and Likens 1979), reducing recruitment (Harvey 1987), and mediating species coexistence (Hemphill and Cooper 1983; Power and Stewart 1987; Meffe 1984). More flood-prone streams may also provide preferential habitat for highly mobile and generalist taxa (e.g. Scarsbrook and Townsend 1993; Poff and Allan 1995).

The Little Patuxent River (and other perennial runoff streams) is presently characterized by moderately high flood frequency with low predictability and thus represents a relatively hydrologically variable system (Poff and

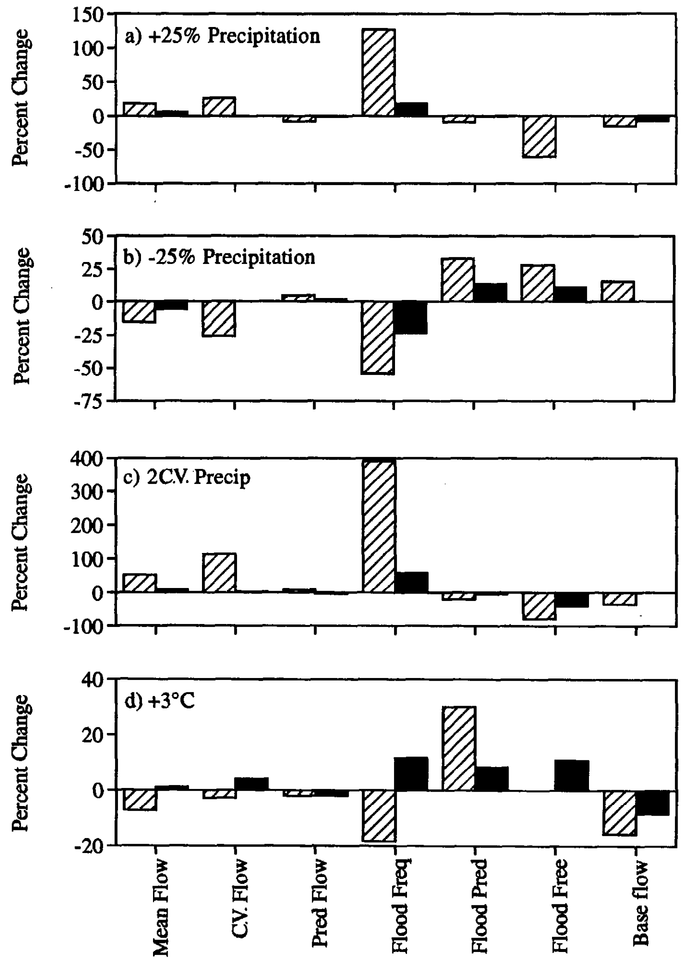

Fig. 3. Responses of seven hydrological variables in the Little Patuxent (hatched bars) and Independence Rivers (solid bars) to four scenarios of climate change: 25% increase in precipitation; 25% decrease in precipitation; doubling of the C.V. in precipitation; temperature increase of 3°C. Variables are mean annual flow, C.V. of daily flow, predictability of flow, flood frequency, flood predictability, flood-free period, and baseflow stability. Note differences in scale for y-axis.

Ward 1989). Climate change could either increase or decrease this variability, with differing ecological implications. An increase in flood disturbance frequency, coupled with a decrease in flood predictability, would generate increased hydrological variability; species favored under more stable hydrological conditions could be at a selective disadvantage in such a modified regime. Such increased variability was observed under two climate change scenarios: +25% precipitation and doubling precipitation variation (Fig. 3a,c). However, ecological resilience to intensified hydrological variability could be high in this stream because the Little Patuxent is already relatively variable, suggesting that the resident fauna may also be adjusted to high hydrological variability.

By contrast, a reduction in flood frequency could result in marked ecological adjustments to a historically flashy hydrograph. The climate change scenario of a 25% reduction in precipitation reduced the flood frequency and increased flood predictability and flood-free period, suggesting an increase in flood seasonality in this stream under this scenario. A reduction in the C.V. of streamflow further suggests that this stream would become less variable should precipitation inputs decline. The scenario of a 3°C temperature elevation also produced a similar, but less intense, dampening of hydrological variability. This climate-induced "stabilization" of the stream hydrograph could result in increasing habitat and resource stability, which would presumably allow species interactions to intensify and thus favor species that perform well in relatively stable environments. For example, Poff and Allan (1995) found that as hydrological stability increased across a set of 34 streams in the upper Midwest, the proportion of resource and habitat specialists in the fish community increased. However, they also found that baseflow stability was a very important correlate of fish community structure because it indicates the extent to which a stream will stop flowing during a low-flow season. Under the scenario of a 3°C increase, low-flow levels in the Little Patuxent decreased, suggesting the possibility that lower flows coupled with higher water temperature could provide strong seasonal selective forces that would favor more tolerant and generalist species, at least for fish (cf. Poff and Allan 1995).

The Independence River is a snow+rain stream characterized by a flood regime of high frequency but moderately high seasonality (Poff and Ward 1989). An increase in flood frequency coupled with a reduction in seasonality could have significant implications in this stream. Research in snowmelt streams has shown that high flows can result in severe population reductions both of vulnerable young-of-year life stages (Seegrist and Gard 1972) and older age-class fish (Erman et al. 1988). A scenario where winter precipitation switched from snow to rain would cause diminished storage and winter runoff—a rare event in the historical record for this stream. A simulated increase of 3°C did increase flood frequency and flood predictability slightly, indicating that additional floods resulted but that they remained clustered around the time of snowmelt rather than occurring earlier in the winter. It is not clear how well any potential ecological adjustments to such small changes (<12%) could be separated from background variation.

The most disruptive scenario for the Independence River would seem to be the doubling of precipitation variability because it increased flood frequency dramatically and greatly reduced the relatively predictable nonflood season (summer months) (Fig. 3d). Increased flooding during a period that has historically been a nonflood period has the strong potential to disrupt seasonal ecological processes (e.g. "predictable" recruitment of vulnerable life stages; cf. Seegrist and Gard 1972). Flood frequency also increased under the scenario of +25% precipitation but the flood-free period did not decline, indicating that flooding increased during the present predictable snowmelt season.

A 25% reduction in precipitation resulted in a regime less flood-disturbed but more predictable, suggesting that fewer floods would occur in summer months relative to the snowmelt period. One potential ecological consequence of this scenario is a reduction in the annual maximum flow (which occurs during snowmelt) of >7%. To the extent that high flows are important in channel formation and maintenance (and hence habitat dynamics for fluvial species), an annual reduction in stream power could have subtle ecological consequences. For example, channel bars might become more stable and promote the persistence of woody riparian vegetation, as has been observed in other regions where flood peaks have been artificially reduced by regulation (e.g. Williams 1978; Ligon et al. 1995). A similar concern arises for the Little Patuxent, which showed a reduction of almost 40% in annual maximum flow as a result of a 25% reduction in precipitation.

Model limitations—The projected changes in hydrologic regimes in the Little Patuxent and Independence Rivers under the provided scenarios of climate change are based on the assumption that the processes generating runoff in the basin reflect only prevailing thermal and precipitation regimes. For example, CO_2 enrichment increases temperature and prolongs the growing season, thus increasing evapotranspiration (ET). Potential direct effects of CO_2 enrichment, such as stimulation of plant growth rates, could also increase ET and lead to reduced streamflow, but the model does not incorporate such responses. The fact that the ANN does not rely on mechanistic response can however, be viewed as an advantage because it does not require that assumptions be made about specific indirect effects that may result from scenarios of climate change. Further, because this technique is not mechanistic, it does not require extensive parameter estimation—a modeling process that may result in large propagation of errors. The relative ability of ANNs vs. more mechanistically based hydrological models to simulate hydrological responses of stream basins is an open research question.

Conclusions

The effects of simulated climate change scenarios differed markedly between our two streams, with the rainfall-dominated Little Patuxent exhibiting greater relative response to climate change than the Independence River. The Independence River was relatively buffered against simulated climate change in that it largely retained its characteristic snowmelt hydrology despite increases in temperature or precipitation variation. Our simulated hydrological results suggest that these two common hydroclimatological stream types in the northeastern U.S. may have different ecological responses to climate change, primarily through changes in the frequency and timing of flooding relative to historical flood regimes.

Given the uncertainty about how climate regimes are likely to change at a regional scale, our assumptions about climatic change are simplifying. In the Independence River, for example, even with an increase in 3°C, the hydrograph remains relatively stable because snow continues to accumulate during winter and melt in a peak during late spring. However, the *timing* of thermal elevations could have very significant hydrological effects. For example, incursions of moist southerly air masses in winter (due perhaps to frequent shifts in the jet stream) could produce winter rains that would prevent snowpack accumulation. These periodic temperature excursions would dramatically alter the relatively predictable hydrological features of this stream. These more complicated scenarios deserve closer attention.

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