# Predicting Ecological Flow Regime at Ungaged Sites: A Comparison of Methods

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## Abstract

Nineteen ecologically-relevant streamflow characteristics were estimated using published rainfall-runoff and regional regression models for six sites with observed daily streamflow records in Kentucky. The regional regression model produced median estimates closer to the observed median for all but two characteristics. The variability of predictions from both models was generally less than the observed variability. The variability of the predictions from the rainfall-runoff model was greater than that from the regional regression model for all but three characteristics. Eight characteristics predicted by the rainfall-runoff model display positive or negative bias across all six sites; biases are not as pronounced for the regional regression model. Results suggest that a rainfall-runoff model calibrated on a single characteristic is less likely to perform well as a predictor of a range of other characteristics (flow regime) when compared to a regional regression model calibrated individually on multiple characteristics used to represent the flow regime. Poor model performance may misrepresent hydrologic conditions, potentially distorting the perceived risk of ecological degradation. Without prior selection of streamflow characteristics, targeted calibration, and error quantification, the widespread application of general hydrologic models to ecological flow studies is problematic.

## Introduction

Streamflow is generally recognized to be a critical determinant of ecological health (Poff *et al.*, 1997; Arthington *et al.*, 2006; Carlisle *et al.*, 2011; Chinnayakanahalli *et al.*, 2011). The overall distribution of streamflow comprises thousands of individual streamflow characteristics, including high and low extremes and details of timing and variability of flow conditions. The suite of streamflow characteristics whose alteration is likely to produce an observable ecological effect constitutes the ecological flow regime (Arthington *et al.*, 2006; Postel and Richter, 2003; Knight *et al.*, 2011). Detailed understanding of how flow affects ecological conditions remains an open scientific challenge, in part because observed hydrologic data are unavailable for many ecological sampling locations (Knight *et al.,* 2008; Poff *et al.*, 2010; Poff and Zimmerman, 2010). Absent observed data, hydrological models are widely cited as a means to predict streamflow at ecological sampling sites and relate estimated streamflow to ecological conditions (Arthington *et al.*, 2006; Carlisle *et al.*, 2010; Knight *et al.*, 2011).

Knight *et al.* (2011) identify two distinct modeling approaches that can be applied to ecological flow studies. The approach most commonly cited in ecological flow literature is the use of numerical rainfall-runoff models to simulate hydrographs, typically for daily time steps across time periods of one to several decades (Williamson *et al.*, 2009; Poff *et al.*, 2010). Descriptive streamflow statistics (streamflow characteristics) are then calculated from the simulated hydrographs and analyzed for relationships to ecological data. An alternative approach is to identify specific streamflow characteristics of interest and estimate them directly through regional regression methods, typically some variant of multivariable linear regression on basin characteristics (Sanborn and Bledsoe, 2006; Carlisle *et al.*, 2010; Knight *et al.,* 2011).

As noted by Knight *et al.* (2011), statistical estimation of streamflow characteristics has received only limited application in ecological flow studies but has been the standard approach for estimating traditional hydrologic characteristics for decades (Riggs, 1973; Tasker, 1982; Tasker and Stedinger, 1989; Tasker and Slade, 1994; Tasker *et al.*, 1996; Law and Tasker, 2003; Law *et al.*, 2009). The question of the relative accuracy and reliability of these two modeling approaches is of considerable interest in designing ecological flow studies, but has rarely been addressed directly because few basins have been modeled using both approaches.

Key Words

ecological flows, environmental flows, watershed modeling, streamflow characteristics, ecological flow regime, ungaged basins

In this paper, we investigate the accuracy and reliability of published rainfall-runoff (Williamson *et al.*, 2009) and regional regression (Knight *et al.*, 2011) models to estimate 19 streamflow characteristics proposed by Knight *et al.* (2011) as having presumptive ecological relevance. These 19 streamflow characteristics describe a suite of flows that represent the ecological flow regime (Knight et al., 2011). The two regionally-calibrated models overlap geographically in the portion of southern Kentucky lying within the Tennessee and Cumberland River basins (Figure 1). However, the two models are calibrated to different levels of hydrologic specificity. The rainfall-runoff model was calibrated on the mean daily discharge and provides a general estimator of hydrologic response, whereas the regional regression model was calibrated for each of 19 streamflow characteristics specifically selected for presumed ecological relevance. Using both models, streamflow characteristics were predicted for six catchments (Table 1) and compared to observed streamflow characteristics calculated from 22 to 68 years of recorded daily streamflow. Following Beven (1989) and Jakeman and Hornberger (1993), we hypothesize that a rainfall-runoff model is unlikely to provide reliable estimates of streamflow characteristics other than for those on which it was calibrated and would therefore be of limited use in predicting ecological flow regime.

## Hydrologic Models in Ecological Flow Studies

Rainfall-runoff models are appealing in ecological flow studies largely because of the flexibility they provide. Any number of streamflow characteristics can be calculated from a simulated streamflow time series without prior knowledge of their ecological relevance. Unlike traditional rainfall-runoff models, which were constrained to simulate streamflow at predetermined nodes, more sophisticated models are now able to simulate flows at any point along a stream reach (Williamson *et al.*, 2009). Additionally, rainfall-runoff models allow for scenario analysis in which inputs and parameters are varied to reflect changing environmental conditions.

Weaknesses of rainfall-runoff models have been discussed at length in the hydrologic modeling literature (e.g. Duan *et al.*, 2006; Kirchner, 2006; Clarke, 2008; Kavetski and Clark 2011). These weaknesses include poorly constrained parameter estimation (Hogue *et al.*, 2004; Duan *et al.,* 2006; Schaake *et al.*, 2006), inadequate quantification of uncertainty (Beven, 2006; Andreassian *et al.*, 2007; Sivapalan, 2009), conceptual errors in model structure and parameterization (Kirchner, 2006), and computational errors (Kavetski and Clark, 2011). Application of rainfall-runoff models to uncalibrated

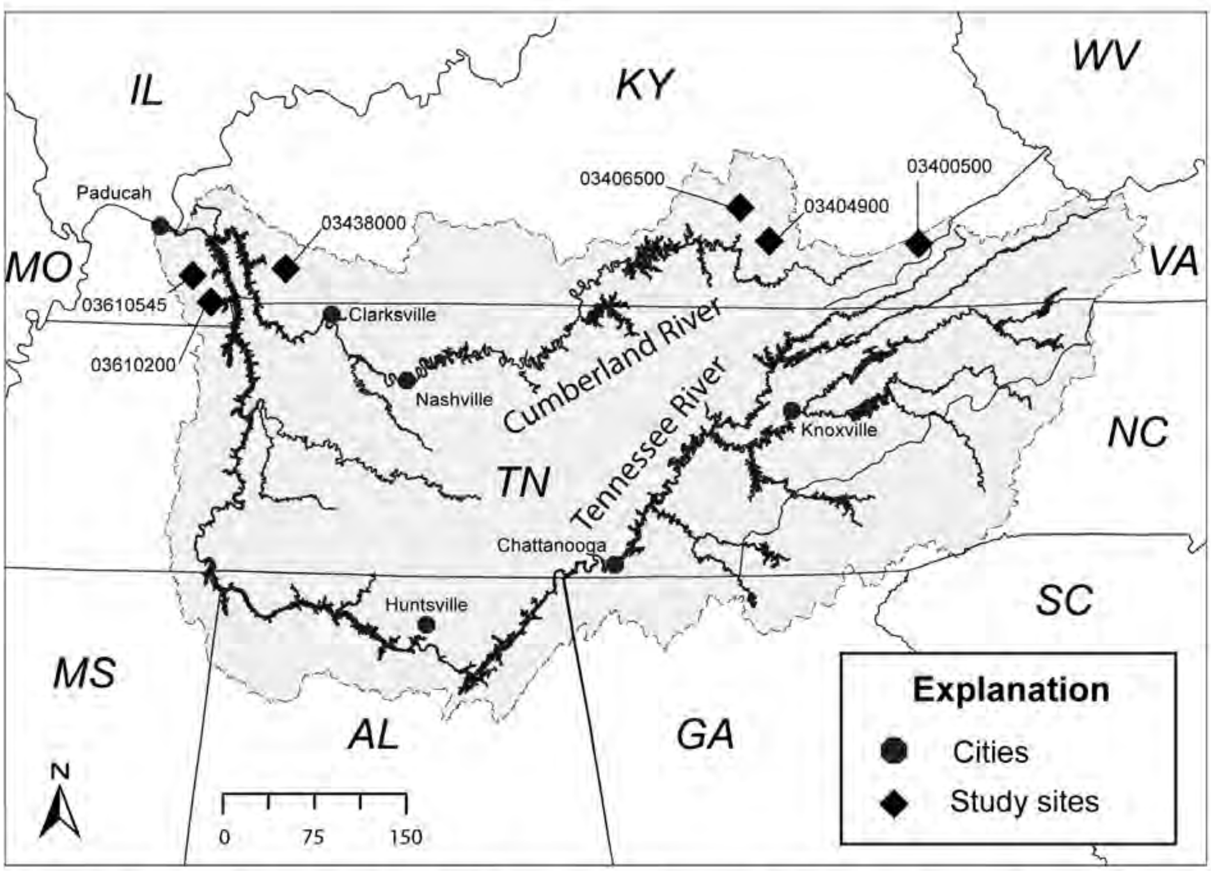


Figure 1. Six watersheds with observed daily streamflow data exist in the geographic overlap of the rainfall-runoff model (Kentucky) and regional regression model (Cumberland and Tennessee River basins). Sites listed in Table 1

sites implicitly extrapolates calibration throughout the modeled area with little prospect of evaluating error or uncertainty. In addition, many rainfall-runoff models are calibrated on mean daily discharge without respect to other aspects of the flow regime, such as extreme low or high flow conditions. A few ecological flow studies begin to address some of these issues by explicitly acknowledging the need to bound uncertainty (Acreman *et al.*, 2009) or to incorporate model error in the analysis (Black *et al.*, 2005). However, ecological flow methodologies generally make little effort to recognize and address these issues (e.g. Richter *et al.*, 1996; Molnar *et al.*, 2002; Kennen *et al.*, 2008; Poff *et al.*, 2010).

Regional regression modeling is an alternative approach for predicting streamflow characteristics. Regional regression models are routinely used to predict flood magnitude and frequency, such as the 100-year flood, and low flow and flow-duration statistics, such as the mean summer streamflow (Riggs, 1973; Tasker, 1982; Tasker and Stedinger, 1989; Tasker and Slade, 1994; Tasker *et al.*, 1996; Law and Tasker, 2003; Law *et al.*, 2009). Such models form the basis for flood insurance and water-supply planning across much of the world. Regional regression methods predict average and extreme flow conditions through interpolation and include well-established tests of accuracy. Also, regional regression techniques can be applied at any point along a stream reach. A chief weakness of regional regression models is their relative inflexibility; because the models are built for specific sets of streamflow characteristics, new models must be developed if subsequent analyses indicate that streamflow characteristics outside the original set are required. Few ecological flow studies have utilized regional regression approaches to relate basin and climate attributes to ecologically relevant streamflow conditions (e.g., Sanborn and Bledsoe, 2006; Carlisle *et al.,* 2010; Knight *et al.,* 2011).

# Methods

Our analysis compares streamflow characteristics estimated from two published models to the same streamflow characteristics calculated from observed data. Both models were applied to the same six basins (Table 1) using input data and model specifications unaltered from their published versions, including the period of simulation where applicable. Model performance was evaluated based on absolute and percent departures of estimated characteristics from observed.

## Rainfall-Runoff Model

The rainfall-runoff model used for comparison was developed by Williamson *et al.* (2009) for Kentucky and is based on TOPMODEL code (Beven and Kirkby, 1979; Wolock, 1993). The model consists of an integrated database of spatially distributed basin attributes and algorithms to compute daily streamflow based on rainfall interpolated from observed records and estimated from high-resolution radar. The model predicts runoff separately for karst and non-karst areas and then sums the results for a final estimate of daily streamflow. The non-karst portion of the model uses conventional TOPMODEL methodology that integrates hillslope dynamics with soil parameters and includes basin-wide water withdrawals and discharges (Williamson *et al.,* 2009). The karst portion implements a modified TOPMODEL approach that prescribes a unique runoff response to sinkhole-drained features. Thirty-one basins (ranging from 17 to 1,564 square kilometers) were used to develop, calibrate, or test the model (Williamson *et al*., 2009). Several statistics were used to calibrate and evaluate performance of the non-karst portion of the model, and included bias (mean 0.10±0.18,), root mean square error (mean 2.47±0.98) and correlation (mean 0.73±0.10) (Williamson *et al.,* 2009). Two of the six sites used in our evaluation were among the 31 basins used to develop the model.

**Table 1.** List of study sites, gage station identification number, drainage area of basin and length of observed daily streamflow record. Average depature is the average of all streamflow characteristic depatures (absolute values) at each site, for the rainfall-runoff model and the regional regression model. RA8 [flow direction reversals]. Units: square kilometers [$km^2$], percent [%]

| Site name | USGS gage number | Basin area ($km^2$) | Observed data range | Average departure (%) rainfall-runoff / regression | |
|---|---|---|---|---|---|
| | | | | with RA8 | without RA8 |
| Poor Fork at Cumberland, KY | 03400500 | 213 | 1941 - 1992 | 97 / 21 | 24 / 21 |
| Lynn Camp Creek at Corbin, KY | 03404900 | 137 | 1974 - 2005 | 119 / 26 | 43 / 27 |
| Rockcastle River at Billows, KY | 03406500 | 1,564 | 1937 - 2005 | 143 / 26 | 79 / 27 |
| Little River near Cadiz, KY | 03438000 | 489 | 1941 - 2005 | 67 / 16 | 42 / 14 |
| Clarks River at Almo, KY | 03610200 | 299 | 1983 - 2005 | 117 / 44 | 41 / 46 |
| West Fork Clarks River near Brewers, KY | 03610545 | 177 | 1969 - 1994 | 88 / 21 | 32 / 22 |

In this study, we used the rainfall-runoff model to simulate daily mean streamflow at six sites for the period 1948 to 2006. For computation of streamflow characteristics, this output was censored to include only the date range matching the observed period of record at each site (Table 1).

### Regional Regression Model

The regional regression model used in this study was developed for the Cumberland and Tennessee River basins and estimates specific streamflow characteristics directly through linear multivariate regression equations (Knight *et al.,* 2011). Independent variables used in the regional regression model represent four categories: (1) climate data, such as monthly mean precipitation, (2) land use percentages, such as percent forest and agriculture, (3) physical landscape features, such as mean elevation, and (4) regional indicators, such as percent basin within a given ecoregion. The regional regression model consists of 19 separate multivariate regression equations, each of which predicts a single streamflow characteristic. Each equation contains 6 to 12 independent variables derived from GIS data layers (Knight *et al.,* 2011). All six sites used in this study (Figure 1) are among the 231 sites in the Tennessee and Cumberland River basins used to develop the regional regression model (Knight *et al.,* 2011).

### Calculating Streamflow Characteristics

For each of the six sites (Table 1), 19 streamflow characteristics were computed in three sets: observed, rainfall-runoff model estimates, and regional regression model estimates. Streamflow characteristics describe aspects of ecological flow regime (definitions in Appendix A) and are identified as having ecological significance in the Tennessee River basin (Knight *et al.*, 2008; 2011). The Hydrologic Integrity Tool (Henriksen *et al.*, 2006) was used to calculate streamflow characteristics from observed streamflow data and from the estimated streamflow from the rainfall-runoff model. The same streamflow characteristics were predicted directly by the regional regression model. At each site, the percent differences between predicted and observed streamflow characteristics were calculated for both models [(model prediction – observed) / observed * 100].

### Comparison of Model Estimates

All model estimates of streamflow characteristics have an element of uncertainty. In addition, the inherent variability of streamflow introduces uncertainty independent of model error. For example, mean annual streamflow at a site differs depending on the period of record chosen. Kennard *et al.* (2010) estimated a 20 to 30 percent difference for a variety of streamflow characteristics when comparing a 75-year daily record to a 15-year or 30-year period. For this paper, we adopted this band of hydrologic uncertainty (+/- 30 percent) for comparing departures of estimated values from observed streamflow characteristics.

## Results

Observed and predicted streamflow characteristics typically vary over one order of magnitude (Table 2). The rainfall-runoff model underestimates the observed variability (predicted range of estimates is narrower than observed range) for all but three characteristics. The regional regression model underestimates the observed variability for all but two characteristics and generally has a narrower predicted range than the rainfall-runoff model (Table 2). Mean annual runoff (MA41) had a narrower observed range than all but two characteristics, which was closely approximated by the regional regression model and underestimated by about 40 percent by the rainfall-runoff model. The greatest variation in ranges was within the streamflow magnitude characteristics (Table 2).

Considered across all 228 trials (19 characteristics, 2 models, 6 basins), no basin or group of basins stands out in terms of overall model accuracy (Table 2). In contrast, one or both models generally predicted some characteristics more accurately than others. For the rainfall-runoff model, eight streamflow characteristics display a positive or negative bias across all six sites. The rainfall-runoff model over-predicted E85, Sep_med, TA1, RA7 and RA8 and under-predicted ML18, DL6 and TH1 (Table 2) at all six sites. Biases are not as pronounced for the regional regression model (Table 2).

## Model Performance

The regional regression model generally provides more accurate predictions than the rainfall-runoff model (Figure 2A). Median departures for 13 of 19 predicted streamflow characteristics from the rainfall-runoff model were outside the +/- 30 percent band of hydrologic uncertainty described above (Figure 2A). Most of these departures were between 30 and 50 percent and a few were greater than 100 percent. In contrast, for the regional regression model, median departures for only two characteristics fell outside the band of hydrologic uncertainty. Twelve departures were less than 10 percent (Figure 2A).

Three characteristics, RA8, E85, and Sep_med, represent the largest departures for the rainfall-runoff model. RA8 (average number of days per year when the slope of the hydrograph changes sign), indicated a deficiency (1,342 percent departure) in the rainfall-runoff model and plotted outside the range of Figure 2A. This deficiency is consistent with other studies concerning the predictive ability of regression and simulation models to describe rate and frequency of daily rises and falls (Richter *et al.*, 1997). For both models, the large relative departures of E85 (streamflow exceeded 85 percent of the time) and Sep_med (median September daily streamflow) reflect the small absolute magnitudes of these characteristics (Figure 2A and Table 2).

The range of departures and lack of uniformity for a given site indicate a basic problem in the application of any model: calibration on any single characteristic cannot be

**Table 2.** Observed and predicted streamflow characteristics for six sites used in this study (see Table 1) with median values and standardized ranges (Range = maximum minus minimum normalized by median). See Appendix A for streamflow characteristic definitions. Units: cfsm [cubic feet per second per square mile], % [percent], Q/day [flow units per day], n/yr [number per year], no units indicated [unitless], days [Julian day].

| | | Magnitude | | | | | | | Frequency | | | Duration | | | Timing | | | Rate of Change | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | E85 | MA26 | MA41 | MH10 | ML18 | ML20 | SEP_med | FH6 | FH7 | FL2 | DH13 | DH16 | DL6 | TA1 | TH1 | TL1 | RA5 | RA7 | RA8 |
| | Site | cfsm | % | cfsm | cfsm | % | | cfsm | n/yr | n/yr | | | % | % | | days | days | | Q/day | n/yr |
| Observed | Range | 1.367 | 0.999 | 0.263 | 5.598 | 0.434 | 0.967 | 1.469 | 0.710 | 0.886 | 0.372 | 1.747 | 1.143 | 1.049 | 0.511 | 0.631 | 0.139 | 0.170 | 0.804 | 1.371 |
| | Median | 0.107 | 99.0 | 1.52 | 275 | 74.8 | 0.289 | 0.117 | 15.64 | 11.89 | 40.5 | 9.84 | 30.2 | 50.34 | 0.376 | 51.6 | 263 | 0.271 | -0.148 | 9.95 |
| | 03400500 | 0.207 | 76.4 | 1.7 | 186 | 56.8 | 0.417 | 0.231 | 13.00 | 7.81 | 37.6 | 6.31 | 24.3 | 47.6 | 0.399 | 57.5 | 270 | 0.271 | -0.134 | 8.76 |
| | 03404900 | 0.104 | 102.2 | 1.62 | 203 | 82.5 | 0.279 | 0.117 | 18.97 | 12.19 | 41.6 | 8.11 | 21.9 | 94.4 | 0.260 | 49.6 | 249 | 0.274 | -0.211 | 9.65 |
| | 03406500 | 0.061 | 95.8 | 1.57 | 1666 | 76.4 | 0.298 | 0.060 | 13.48 | 11.59 | 39.3 | 10.51 | 29.1 | 90.3 | 0.396 | 53.6 | 264 | 0.280 | -0.159 | 10.26 |
| | 03438000 | 0.139 | 71.8 | 1.47 | 347 | 50.1 | 0.428 | 0.160 | 9.77 | 7.89 | 51.6 | 9.18 | 56.5 | 41.5 | 0.452 | 59.4 | 280 | 0.245 | -0.092 | 22.40 |
| | 03610200 | 0.067 | 170.6 | 1.38 | 627 | 75.8 | 0.149 | 0.061 | 20.87 | 18.35 | 52.7 | 23.50 | 31.4 | 53.1 | 0.356 | 41.1 | 261 | 0.271 | -0.154 | 9.53 |
| | 03610545 | 0.110 | 136.6 | 1.33 | 124 | 73.8 | 0.228 | 0.117 | 17.80 | 15.40 | 38.2 | 15.37 | 31.5 | 43.9 | 0.332 | 26.8 | 243 | 0.234 | -0.142 | 11.14 |
| Rainfall-runoff | Range | 0.860 | 0.444 | 0.153 | 2.168 | 0.959 | 0.486 | 0.848 | 0.448 | 0.806 | 0.239 | 0.447 | 0.438 | 0.568 | 0.578 | 1.269 | 0.079 | 0.121 | 0.559 | 0.157 |
| | Median | 0.262 | 78.7 | 1.75 | 491 | 37.1 | 0.397 | 0.276 | 13.5 | 7.98 | 39.7 | 6.77 | 43.5 | 38.2 | 0.431 | 22.7 | 256 | 0.281 | -0.106 | 140.53 |
| | 03400500 | 0.258 | 91.3 | 1.73 | 317 | 28.2 | 0.362 | 0.263 | 14.3 | 8.89 | 43.6 | 7.537 | 28.6 | 22.0 | 0.459 | 21.3 | 252 | 0.281 | -0.102 | 131.64 |
| | 03404900 | 0.266 | 78.2 | 1.62 | 209 | 37.1 | 0.411 | 0.289 | 16.7 | 7.82 | 40.1 | 6.009 | 31.4 | 43.7 | 0.403 | 22.5 | 257 | 0.294 | -0.109 | 153.70 |
| | 03406500 | 0.311 | 56.3 | 1.56 | 1273 | 35.0 | 0.549 | 0.311 | 10.7 | 4.00 | 44.8 | 5.306 | 45.7 | 37.7 | 0.584 | 43.6 | 272 | 0.271 | -0.073 | 141.72 |
| | 03438000 | 0.356 | 56.3 | 1.83 | 665 | 37.1 | 0.555 | 0.348 | 11.5 | 4.19 | 35.3 | 5.305 | 47.7 | 24.5 | 0.539 | 43.3 | 272 | 0.261 | -0.060 | 139.33 |
| | 03610200 | 0.131 | 85.3 | 1.78 | 728 | 63.8 | 0.362 | 0.114 | 14.5 | 10.44 | 39.4 | 8.330 | 41.9 | 42.4 | 0.371 | 22.9 | 253 | 0.295 | -0.111 | 150.26 |
| | 03610545 | 0.142 | 79.3 | 1.78 | 219 | 51.3 | 0.383 | 0.136 | 12.7 | 8.15 | 36.2 | 7.522 | 45.0 | 38.6 | 0.335 | 14.7 | 255 | 0.281 | -0.119 | 134.22 |
| Regional regression | Range | 0.557 | 0.311 | 0.279 | 3.236 | 0.358 | 0.217 | 0.433 | 0.256 | 0.349 | 0.152 | 0.438 | 0.390 | 0.561 | 0.293 | 0.299 | 0.046 | 0.171 | 0.265 | 0.151 |
| | Median | 0.160 | 99.5 | 1.50 | 357 | 59.0 | 0.336 | 0.182 | 14.0 | 11.14 | 44.6 | 9.65 | 33.9 | 56.6 | 0.356 | 47.0 | 261 | 0.256 | -0.140 | 11.41 |
| | 03400500 | 0.159 | 89.7 | 1.80 | 368 | 64.4 | 0.341 | 0.188 | 13.0 | 9.31 | 40.2 | 8.860 | 25.9 | 70.3 | 0.340 | 40.4 | 264 | 0.270 | -0.154 | 10.09 |
| | 03404900 | 0.208 | 99.0 | 1.50 | 177 | 49.2 | 0.338 | 0.227 | 16.4 | 11.09 | 42.1 | 9.290 | 29.6 | 51.4 | 0.371 | 48.6 | 266 | 0.272 | -0.151 | 11.50 |
| | 03406500 | 0.144 | 94.1 | 1.46 | 1332 | 54.9 | 0.334 | 0.155 | 14.8 | 11.19 | 43.1 | 8.937 | 32.7 | 47.9 | 0.388 | 48.3 | 262 | 0.266 | -0.144 | 11.44 |
| | 03438000 | 0.162 | 100.0 | 1.38 | 346 | 48.3 | 0.382 | 0.175 | 12.8 | 9.56 | 46.0 | 10.018 | 39.1 | 38.5 | 0.410 | 48.8 | 260 | 0.247 | -0.117 | 11.82 |
| | 03610200 | 0.183 | 120.6 | 1.64 | 561 | 63.0 | 0.310 | 0.221 | 15.0 | 13.20 | 47.0 | 13.088 | 35.1 | 61.9 | 0.306 | 34.8 | 254 | 0.228 | -0.132 | 11.38 |
| | 03610545 | 0.118 | 111.1 | 1.50 | 191 | 69.5 | 0.322 | 0.148 | 13.2 | 11.53 | 46.6 | 12.338 | 35.1 | 63.3 | 0.325 | 45.7 | 254 | 0.236 | -0.136 | 11.15 |

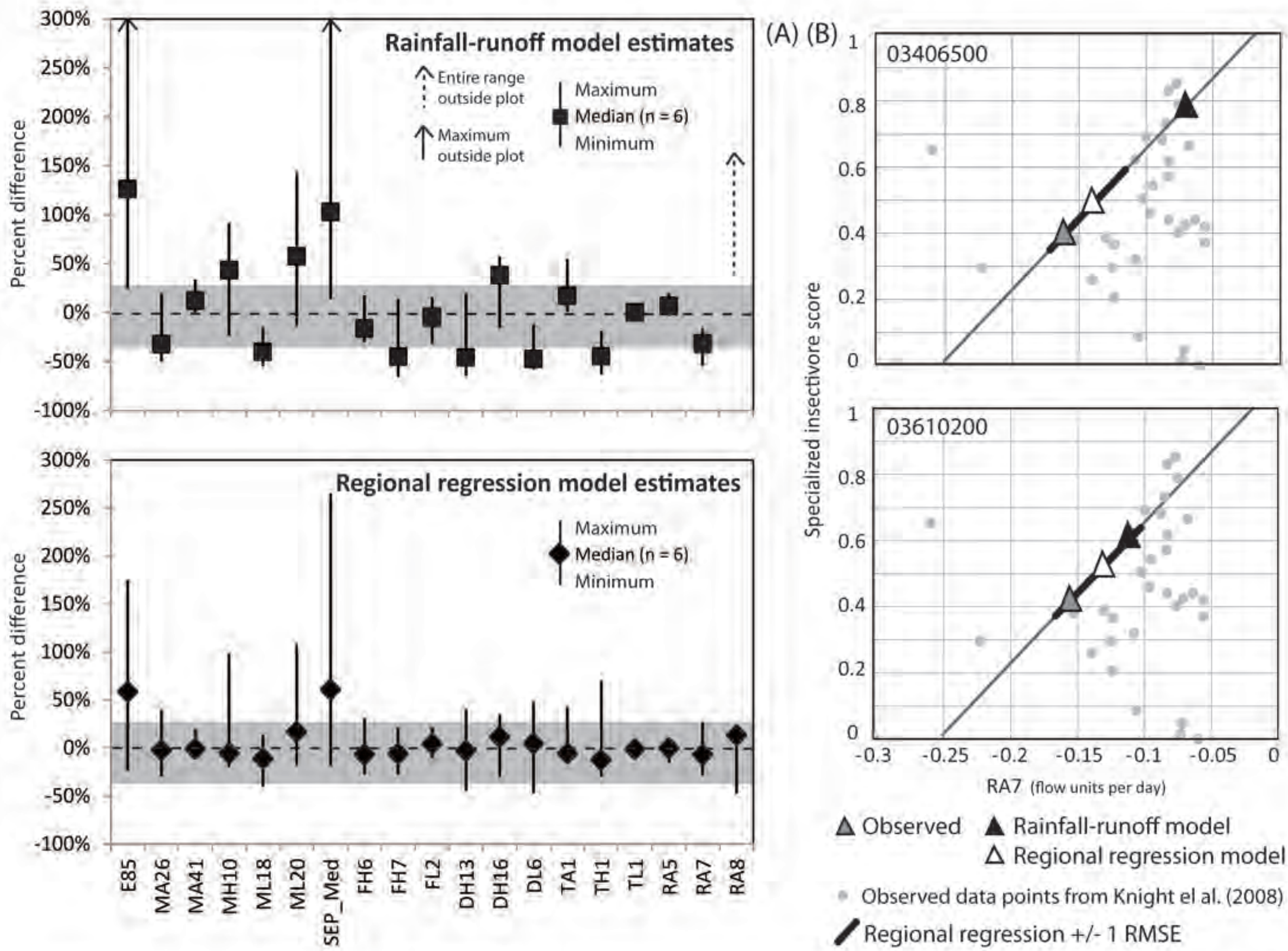


Figure 2. (A) Departures of predicted (rainfall-runoff and regional regression models) from observed values of 19 streamflow characteristics. Vertical lines indicate range of departures from all six sites. Gray bar represents +/- 30 percent difference (band of hydrologic uncertainty). For rainfall-runoff model, maximum departures for E85 and Sep_Med are 408% and 422%, respectively. Minimum, maximum and median departures for RA8 predictions (rainfall-runoff model) are 522%, 1,493% and 1,342% respectively, and not shown on figure.

(B) Example ecological flow application using a quantile regression relationship between RA7 and specialized insectivore score (Figure after Knight et al. 2008). Gray circles in upper and lower plots are RA7 and specialized insectivore scores for 33 sites in the Tennessee River Valley, 80th percentile quantile (thin gray line) is calculated from this data (for further explanation, see Knight et al. 2008). Regional regression predictions +/- 1 RMSE error bounds (thick black line).

shown to predict other characteristics accurately. In many models, calibration on the mean departures or mean daily discharge may equate to a calibration on MA41 (mean annual runoff). The rainfall-runoff model predicted MA41 within 1 percent of the observed value for three sites (03400500, 03404900, and 03406500) and although the model appears to be well calibrated, departures for other characteristics at these three sites were much greater (Table 2). In fact, the rainfall-runoff model for Rockcastle River at Billows, Kentucky (03406500), a calibration site, predicted MA41 within 1 percent of the observed value but also had the greatest average departure across all characteristics (142 percent, Table 1). The regional regression model avoids this issue by having an independently calibrated equation for each characteristic.

## Implications for Ecological Flow Studies

Ecological flow studies aim to predict the ecological effects of streamflow alteration triggered by changes in land cover, climate, impoundments, water withdrawals, and similar factors (Richter *et al.*, 1996; Richter *et al.,* 1997; Kennen *et al.*, 2008; Carlisle *et al.*, 2010). Among several key issues identified by Knight *et al.* (2011) is the question of which types of conceptual and mathematical models best address the effect of hydrologic alteration on ecologic potential.

The accuracy of streamflow-characteristic predictions is important because of the potential consequences a poor prediction can have on estimates of ecological health. For example, Knight *et al.* (2008) found that the rate of streamflow recession (RA7) is related to the specialized insectivore score using an 80$^{th}$-percentile upper-bound relationship (quantile regression) in the Tennessee River valley

$$Y=1.082+4.26X$$

where X is the predicted streamflow characteristic value, and Y is the resulting specialized insectivore score. This quantile regression line can be seen to represent the potential for specialized insectivore score based on the rate of streamflow recession (Figure 2B). Using this equation, an observed RA7 value of -0.159 (site 03406500) yields a potential insectivore score of 0.405. Predictions of RA7 from the rainfall-runoff model (-0.073) and the regional regression model (-0.144) produce potential specialized insectivore scores of 0.771 and 0.469, respectively; these scores are 90 and 16 percent different, respectively, from the score estimated from the observed streamflow characteristic.

Over or under estimation of RA7 may have the effect of misstating the hydrologic suitability for specialized insectivores (Figure 2B). The steep slope for this linear flow-ecology relationship (Knight *et al.*, 2008) amplifies the influence of prediction error on the resulting estimate of ecological potential. Thus for the regional regression model at this site, a hydrologic error of 9 percent produces a 16 percent overestimation of the potential insectivore score. Additionally, a 54 percent hydrologic error produced by the rainfall-runoff model translates into a 90 percent overestimation of the potential insectivore score at this site. Overstatement of background hydrologic suitability could translate into an understatement of the relative risk of degradation at a site and underestimate the impact of alteration on biota.

One advantage of regression models is a set of well established procedures to quantify error, for example root mean square error (RMSE). In statistical applications, RMSE is the mathematical equivalent of standard deviation and +/- 1 RMSE from predicted values should encompass approximately 68 percent of the observed values. At Clarks River at Almo, Kentucky (03610200), the regional regression model predicted a value of -0.132, with +/- 1 RMSE ranging from -0.106 to -0.163 for RA7 (based on Table 2 in Knight *et al.*, 2011), bracketing the observed value of -0.154 (Figure 2B). Overall, approximately 70 percent of observed streamflow characteristics were encompassed by +/- 1 RMSE from their corresponding predicted value. Applied to ecological flow studies, RMSE can be related to ecological metrics through predicted streamflow characteristics. However, the range of uncertainty in streamflow characteristics and ecological potential has been minimally explored in the literature and without serious assessment of uncertainty, results of ecological flow studies will be open to challenge in public policy and decision-making contexts.

## Conclusion

At the foundation of ecological flow studies is the requirement of reliable estimates of ecologically-relevant streamflow characteristics. Typically, the source of streamflow data for ecological flow studies is a simulated daily hydrograph produced by a rainfall-runoff model. Our analysis challenges the presumed suitability of these models for describing ecological flow regimes at ungaged sites. The regional regression model did not in every case produce better results but it was more reliable overall, was less likely to produce large departures from observed values, and provided some measure of relative uncertainty. Our results highlight the importance of (1) prior selection of modeled streamflow characteristics, (2) targeted model calibration using those characteristics, and (3) quantification of model error. Without such provisions, widespread application of general hydrologic models to ecological flow studies is problematic. The difference in model performance does not necessarily indicate any shortcoming in this rainfall-runoff model for general hydrologic simulation, but it does point to limitations in how such models can be effectively applied in ecological flow studies.

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**Appendix A.** Definitions of hydrologic metrics predicted using regression analysis. [adapted and modified from Knight *et al.*, 2008].

| | Streamflow characteristics | | Definition (units) |
|---|---|---|---|
| Magnitude | **E85** | – Streamflow value exceeded 85-percent of time | 85-percent exceedance of daily mean streamflow for the period of record normalized by the watershed area (cfsm). |
| | **MA26** | – Variability of March streamflow | Compute the standard deviation for March streamflow and divide by the mean streamflow for March. (percent) |
| | **MA41** | – Mean annual runoff | Compute the annual mean daily streamflow and divide by the drainage area. (cubic feet per second (cfs) per square mile (cfsm)) |
| | **MH10** | – Maximum October streamflow | Maximum October streamflow across the period of record divided by watershed area. (cfsm) |
| | **ML18** | – Variability in base flow | Standard deviation of the ratios of 7-day moving average flows to mean annual flows for each year multiplied by 100. (percent) |
| | **ML20** | – Base flow | Divide the daily flow record into 5-day blocks. Assign the minimum flow for the block as a base flow for that block if 90 percent of that minimum flow is less than the minimum flows for the blocks on either side. Otherwise, set it to zero. Fill in the zero values using linear interpolation. Compute the total flow for the entire record and the total base flow for the entire record. ML20 is the ratio of total flow to total base flow. (dimensionless) |
| | **Sep_med** | – Median September daily streamflow | Calculate the median of daily mean streamflow values for the period of record that occurred in the month of September normalized by watershed area (cfsm). |
| Frequency | **FH6** | – Frequency of moderate flooding (three times median annual flow) | Average number of high-flow events per year that are equal to or greater than three times the median annual flow for the period of record. (number per year) |
| | **FH7** | – Frequency of moderate flooding (seven times median annual flow) | Average number of high-flow events per year that are equal to or greater than seven times the median annual flow for the period of record. (number per year) |
| | **FL2** | – Variability in low-pulse count | Coefficient of variation for the number of annual occurrences of daily flows less than the 25th percentile. (dimensionless) |
| Duration | **DH13** | – Average 30-day maximum | Average over the period of record of the annual maximum of 30-day moving average flows divided by the median for the entire record. (dimensionless) |
| | **DH16** | – Variability in high-pulse duration | Standard deviation for the yearly average high-flow pulse durations (daily flow greater than the 75th percentile). (percent) |
| | **DL6** | – Variability of annual minimum daily average streamflow | Standard deviation for the minimum daily average streamflow. Multiply by 100 and divide by the mean streamflow for the period. (percent) |
| Timing | **TA1** | – Constancy | Measures the stability of flow regimes by dividing daily flows into pre-determined flow classes. (dimensionless) |
| | **TH1** | – Annual maximum flow | Julian date of annual maximum flow occurrence. (Julian day) |
| | **TL1** | – Annual minimum flow | Julian date of annual minimum flow occurrence. (Julian day) |
| Rate of Change | **RA5** | – Number of day rises | Compute the number of days in which the flow is greater than the previous day divided by the total number of days in the flow record. (dimensionless) |
| | **RA7** | – Rate of streamflow recession | Median change in log of flow for days in which the change is negative across the entire flow record. (flow units per day) |
| | **RA8** | – Flow direction reversals | Average number of days per year when flow changes from rising to falling (or from falling to rising). (number per year) |