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Hydrologic Modeling for Flow-Ecology Science

in the Southeastern United States and Puerto Rico



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Abstract

An understanding of the applicability and utility of hydrologic models is critical to support the effective management of water resources throughout the Southeastern United States (SEUS) and Puerto Rico (PR). Hydrologic models have the capacity to provide an estimate of the quantity of available water at ungauged locations (i.e., areas of the country where a U.S. Geological Survey [USGS] continuous record gauge is not installed) and provide the baseline flow information necessary to develop the linkages between water availability and characteristics of streamflow that support ecological communities (i.e., support the development of flow-ecology response models). This report inventories and then directly examines and compares a subset of hydrologic models used to estimate streamflow at a number of gauged basins across the SEUS and PR. This effort was designed to evaluate, quantify, and compare the magnitude of error and to investigate the potential causes of error associated with predicted streamflows from seven hydrologic models of varying complexity and calibration strategy. This was accomplished by computing and then comparing classical hydrologic model fit statistics (e.g., mean bias, coefficient of determination [R^2], root mean squared error [RMSE], Nash-Sutcliffe Efficiency [NSE]) and understanding the bias in the prediction in these and a subset of ecologically relevant flow metrics (ERFMs). Additionally, streamflow predictions from a larger regional-scale hydrologic model were compared to those of several fine-scale hydrologic models under a range of hypothetical climate change scenarios to determine the range of predicted streamflow responses to fixed climate perturbations. A pilot study was conducted using predicted streamflow and boosted regression trees to develop a set of predictive flow-ecology response models to assess the potential change in fish species richness in the North Carolina Piedmont under several scenarios of water availability change. This report is intended to provide a general assessment of all the tools and techniques available to support hydrologic modeling for flow-ecology science in the SEUS and PR. It is our hope that the approach used herein to understand differences in streamflow predictions among a subset of hydrologic models that have been applied in the SEUS for developing flow-ecology response models will provide water resource managers and stakeholders with an informed pathway for developing the capacity to link streamflow and ecological response and an understanding of some of the limitations associated with these type of modeling efforts.

Keywords: Ecological flows, fish species richness, flow alteration, flow-ecology models, hydrologic models, water supply, water withdrawals.

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CHAPTER 1

Introduction

Assessing the impact of flow alteration on aquatic ecosystems has been identified as a critical area of research and a priority science need of the U.S. Department of the Interior Southeast Climate Adaptation Science Center (SCASC). Beginning in 2012, U.S. Department of Agriculture Forest Service scientists collaborated with scientists from the U.S. Geological Survey (USGS) and North Carolina State University in a SCASC-funded project to develop an inventory and evaluation of current efforts and knowledge gaps in hydrologic modeling for flow-ecology studies across the Southeastern United States (SEUS) and Puerto Rico (PR). To accomplish this goal, we synthesized and evaluated hydrologic modeling efforts in the SEUS (including all States of the Southeastern Association of Fish and Wildlife Agencies: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, Missouri, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia) and Puerto Rico. Because this modeling synthesis was performed comprehensively and using a consistent methodology, it will provide Landscape Conservation Cooperatives (LCCs) and resource managers with a useful database of who is doing what, where, how, and how well in terms of hydrologic modeling across the SEUS and PR.

BACKGROUND

River flows are essential for sustaining the health of aquatic ecosystems and maintaining ecosystem services such as water supply for consumptive use. Human activities, including regulation by dams (Biemans and others 2011, Graf 1999, Poff and others 2007), withdrawals (Gerten and others 2008), interbasin transfers (Emanuel and others 2015, Jackson and others 2001), and land cover change (Foley and others 2005) have significantly altered the magnitude and timing of river flows. The health and biotic condition of aquatic ecosystems have declined as a result (Carlisle and others 2010, Dudgeon and others 2006, Poff and Zimmerman 2010, USEPA 2011). In addition to anthropogenic hydrologic alterations, future changes in climate will likely further impact river flows (Georgakakos and others 2014). Assessing the effect of flow alteration on aquatic ecosystems has been identified as a critical area of research in the SEUS (Knight and others 2014, SALCC 2012, SARP 2004), nationally (Carlisle and others 2010, Novak and others 2016), and abroad (Annear and others 2004; Arthington and others 2006, 2018; Poff and

others 2010). The SEUS is recognized as one of the most ecologically rich areas in the world (Masters and others 1998), making it imperative to assess ecological response to flow alteration. As a result, and considering recent droughts and interstate conflict over water availability issues, many States in the SEUS are investigating the implementation of regulatory controls on streamflow alteration in the interest of maintaining a balance between supporting healthy aquatic ecosystems and providing ample water supplies for human use (e.g., NCEFSAB 2013). Reliable, multi-scale hydrologic and ecosystem modeling approaches are needed to accomplish this goal (Poff and others 2010). However, error (i.e., uncertainty or bias) in streamflow predictions by hydrologic models and predictions of ecological response to changes in flow regime with ecological models can be significant and may be compounding, thereby confounding the determination of environmental flow requirements and potentially exposing managers of water resources to litigation by the regulated community.

The Ecological Limits of Hydrologic Alteration (ELOHA) framework (Poff and others 2010) is often used as a basis for developing regional environmental flow requirements. One of the first steps emphasized in the ELOHA process is to develop a hydrologic foundation of simulated baseline and altered streamflow hydrographs. Hydrologic models are commonly used for this purpose because they have the ability to simulate streamflow at varying timescales under baseline conditions and an infinite number of scenarios of flow alteration. Many models have been employed in the SEUS to generate a hydrologic foundation on which to examine and test hypotheses of changes in water availability, land use, and climate.

Major modeling efforts in the SEUS and PR include:

1. The South Atlantic LCC (SALLC) funded a project with The Nature Conservancy and Research Triangle Institute (RTI) to simulate daily flows in the SALCC at a very fine spatial resolution using a rainfall-runoff model (<https://waterfall.rti.org/>).
2. The U.S. Geological Survey is developing multi-resolution daily rainfall-runoff and statistical hydrologic models in the Apalachicola-Chattahoochee-Flint Basin for climate change and ecohydrological assessments as part of the Flint River Science Thrust Project, Southeast Regional Assessment Project (Dalton

and Jones 2010), and the National Water Census (https://www.usgs.gov/mission-areas/water-resources/science/apalachicola-chattahoochee-flint-river-basin-focus-area-study?qt-science_center_objects=0#qt-science_center_objects) (Alley and others 2013). In addition, rainfall-runoff models are under development for Puerto Rico in support of the Caribbean LCC.

3. The U.S. Environmental Protection Agency (USEPA) Global Change Research Program (<http://www.globalchange.gov/agency/environmental-protection-agency>) has contracted with Tetra Tech and others to develop rainfall-runoff models to evaluate the potential effects of climate and land use change on the hydrology and water quality of 20 major U.S. drainage basins, including the Albemarle-Pamlico Basin, Apalachicola-Chattahoochee-Flint (ACF) Basin, and a Georgia-Florida Coastal Plain basin (USEPA 2013).
4. The Georgia Water Resources Institute at Georgia Tech developed a decision-support system (<http://gwri.gatech.edu/research/GWRI/ACFS>) including hydrologic models for the ACF Basin to evaluate water management alternatives under several climate change scenarios (Georgakakos and others 2010).
5. The U.S. Department of Agriculture Forest Service developed a national-scale water balance and flow routing model for the conterminous United States (<https://forestthreats.org/research/tools/WaSSI>) capable of predicting monthly streamflow as influenced by changes in climate, land use, and water withdrawals (Caldwell and others 2012; Sun and others 2008, 2011b). The model is currently under development to predict monthly streamflow in Puerto Rico.
6. Many States have their own hydrologic modeling activities to develop water resource adaptation strategies for responding to environmental change by using various models (Davis 2011). For example, North Carolina is developing models for key basins to ensure sustainable water resources for the future (https://www.ncwater.org/Data_and_Modeling/Tar/).

All of these approaches operate at different resolutions, extents, time periods, and model performance criteria, and take into account different aspects of environmental change (climate, land use, and water availability). A comprehensive synthesis of these efforts is needed so that managers may make informed decisions regarding model use and fully understand the uncertainty associated with their predictions of streamflow and ecological response. Regardless of the hydrologic model used, the model must be able to reasonably replicate streamflow observations at a monthly, daily, or sub-daily timescale to derive ecologically relevant flow metrics (ERFMs) representing

the five primary components of the flow regime (i.e., magnitude, frequency, duration, timing, and rate of change) under historical and current conditions across points of interest for regulation. The model must also predict changes in these metrics as a result of changes in climate, land use, flow regulation, and water withdrawals. Due to the compounding nature of error in flow-ecology modeling, error in hydrologic model prediction of streamflow is often carried through the analysis and should be quantified and reported to avoid misinterpretation or misuse of modeling outcomes.

Given the diversity of hydrologic models available for water supply and environmental flow studies, it would be useful for resource managers to have some sense of the relative error in streamflow predictions among commonly used hydrologic models in terms of classical fit statistics of streamflow observations (e.g., bias, Nash-Sutcliffe Efficiency [NSE]) and ERFMs. Unfortunately, the determination as to which model is best suited for answering a particular ecological question or even whether one model is better suited for a specific region or for a specific portion of the flow regime (e.g., low flows) is hampered by a lack of comprehensive model comparison studies (Knight and others 2012). In addition, the type of hydrologic model, model inputs (e.g., climate, soils, land cover), and calibration strategy likely influence the capacity of a given hydrologic model to predict observed streamflow.

Leveraging the benefits of utilizing large-scale models with smaller scale, high-resolution models concurrently, rather than using each approach in isolation, has the potential to allow more robust environmental change assessment studies that maintain a better balance between the availability of water to support aquatic assemblages while conserving water for long-term human needs across broad regions. For example, the Water Supply Stress Index (WaSSI) model (Caldwell and others 2012, Sun and others 2011b) is a regional-scale monthly water balance and flow routing model that has been used to evaluate the effects of environmental change on water supply and river flows. The model is typically run uncalibrated using off-the-shelf databases and thus could be used to assess broad-scale environmental change and identify specific areas of concern ("hot spots") where the combined effects of land cover change, climate change, and/or flow alteration may threaten water resources. Fine-scale, physically based models of higher temporal resolution (e.g., Hydrological Simulation Program-Fortran [HSPF], Precipitation-Runoff Modeling System [PRMS], Soil and Water Assessment Tool [SWAT], etc.) could then be applied to those areas of concern to provide higher resolution quantitative estimates

of changes in water supply and ERFMs using more site-specific inputs. To apply such a multi-scale modeling approach, the variability of predicted streamflow response to different stressors across large- and fine-scale models must first be assessed. For example, for a given change in precipitation, do the models predict similar changes in streamflow?

RESEARCH OBJECTIVES

The objectives of this study were to (1) inventory existing hydrologic modeling efforts in the SEUS and PR, (2) evaluate and compare the performance of participating hydrologic models in predicting observed streamflows at multiple scales, (3) demonstrate the feasibility of using regional- and fine-scale models to identify unique areas of concern and understand fine-scale hydrologic dynamics for climate change assessment, respectively, and (4) conduct a pilot study at the regional scale using flow-ecology response modeling to assess the effect of changes in water availability in the North Carolina Piedmont based on a series of plausible change scenarios including climate, land use, and water withdrawals.

For objective 1, modeling efforts in the region were inventoried by contacting Federal and State agencies, members of academia, and environmental consultants to create a database of models used in the SEUS and PR. Information collected included the organization performing the study, intended purpose, model framework, spatial extent, spatial and temporal resolution, time period simulated, model inputs, model outputs (e.g., flow, water quality, ecosystem response), elements of environmental change represented (e.g., climate change, land use change, withdrawals/flow regulation), and validation procedure, criteria, and results.

For objective 2, a subset of the model developers attended a workshop where attendees compared and contrasted the hydrologic output of both coarse-scale monthly models and fine-scale daily models, quantifying their ability to estimate observed flows over a common time period for selected basin(s) in the SEUS. We did not evaluate model applications in PR because no models had streamflow predictions at gauged locations at the time of this study.

For objective 3, streamflow predictions from WaSSI, a regional-scale model, were compared to those of several of the fine-scale models assessed in the model comparison workshop under a range of hypothetical climate change

scenarios, to determine the range of predicted streamflow responses to fixed climate perturbations. Our working hypothesis was that similarly predicted streamflow changes under climate change scenarios among regional- and fine-scale models would provide evidence that these models could be used in combination to identify hot spots of concern and understand unique fine-scale hydrologic dynamics.

For objective 4, a set of predictive flow-ecology response models were developed that assess the potential change in fish species richness in the North Carolina Piedmont under several scenarios of water availability change including streamflow withdrawals, climate change, and land cover change.

RELATIONSHIP TO OTHER STUDIES

Through a partnership between the SALCC and the Southeast Aquatic Resources Partnership (SARP), an inventory of existing models in the SALCC region was completed (Davis 2011). The Appalachian LCC had a similar project with the New York Cooperative Fish and Wildlife Research Unit for the Appalachian LCC region (Fisher and others 2013). The USGS, as part of the WaterSMART Initiative National Water Census, led a multi-model comparison study in the Southeast which was designed to assess the relative uncertainty in hydrologic predictions among several daily and monthly time-step models (Farmer and others 2014). The project described in this report was intended to complement and more broadly encapsulate prior work in the SEUS, including the SALCC hydrologic model inventory, the Appalachian LCC hydrologic model inventory, and the National Water Census model comparison study, and provide additional insights through direct model comparisons, evaluation of model sensitivity, and the development of flow-ecology response models.

ORGANIZATION OF THIS REPORT

Chapters 2–5 of this report summarize the results of each of the research objectives described above. The chapters were written to be “self-contained” and can be read without referring to other chapters. This format was selected to make reading of the report easier. Detailed results, databases, and links to reports may be found online at <https://cascprojects.org/#/project/4f8c6557e4b0546c0c397b4c/5016cacde4b06fb5ce8b7371>.

CHAPTER 2

Inventory of Existing Hydrologic Models in the Southeastern United States and Puerto Rico

INTRODUCTION

There are many researchers, water resource professionals, and environmental flow practitioners developing and applying hydrologic models in the Southeastern United States (SEUS) and Puerto Rico (PR). However, there are few databases that describe the various modeling efforts underway across the region so that resource managers may have access to model outputs to aid in addressing water resource problems. To meet this need, an inventory of current efforts and knowledge gaps in hydrologic modeling for flow-ecology science and environmental change assessment studies across the region was created. This modeling inventory was performed as comprehensively as possible and used a consistent methodology, and thus it will provide Landscape Conservation Cooperatives (LCCs) and resource managers with a useful database of organizations developing hydrologic models for assessing environmental change effects across the SEUS and PR.

METHODS

An inventory of existing hydrologic models in the SEUS and PR was compiled by distributing a brief questionnaire (table 2.1) to contacts at State and Federal agencies, academic institutions, and environmental consultants throughout the region (table 2.2). An initial list of contacts was developed via the professional knowledge of project participants and by using the SEUS Hydrologic Model Assessment compiled by Southeast Aquatic Resources Partnership (SARP) (<https://southeastaquatics.net/resources/pdfs/Hydrologic%20Model%20Assessment%20041411.pdf>). The information requested from these contacts included model developer, intended purpose, model framework, spatial extent, spatial and temporal resolution, time period simulated, model inputs, model outputs (e.g., flow, water quality, ecosystem response), elements of environmental change represented (e.g., climate change, land use change, withdrawals/flow regulation change), and validation procedure, criteria, and results. Questionnaire interviews were primarily conducted by phone, with the exception of a few individuals who

responded to the questionnaire by email. Questionnaire results were stored in a Microsoft® Excel spreadsheet.

RESULTS

The results of the modeling inventory are available at the project web page at <https://cascprojects.org/#/project/4f8c6557e4b0546c0c397b4c/5016cacde4b06fb5ce8b7371>. The model inventory contact list included 95 individuals applying hydrologic models throughout the SEUS and PR. Of the 64 unique organizations solicited, 19 represented Federal agencies, 11 represented State agencies, 32 represented universities, and 2 represented private sector organizations (environmental consultants). Twenty of the individuals agreed to be interviewed or were participants in the model comparison workshop, with two of the individuals using two different models. Respondents used multiple hydrologic models and were working throughout the SEUS and PR (table 2.3). Of these, 16 used rainfall-runoff models (i.e., models that predict streamflow using climate inputs including rainfall), while four of the respondents used statistical models (i.e., estimates of streamflow derived empirically using streamflow records from gauged basins). Thirteen of the respondents represented government agencies, while five and two represented universities and private sector organizations, respectively. Model uses ranged from estimating streamflow under scenarios of changing climate and water use to predicting effects on water quality, aquatic ecosystems, and water availability for humans. Basins in Alabama, Georgia, and North Carolina were the best represented in the survey results (7 or more of the 20 respondents); however, a large proportion of the basins simulated in these States were restricted to the Apalachicola-Chattahoochee-Flint (ACF) Basin. Basins in Arkansas, Kentucky, Louisiana, Mississippi, Missouri, Oklahoma, Texas, West Virginia, and Puerto Rico were least represented (three or fewer respondents). While these results are based on a subsample of modeling efforts in the region, they may suggest areas that are less studied, and thus potential environmental change effects on streamflow may be less understood.

Table 2.1—Questions from hydrologic model inventory questionnaire

1.	What is the name of your model (e.g., WaSSI, PRMS)?
2.	Who developed the model (e.g., individual researcher, agency initiative)?
3.	Who applied the model?
4.	What is the intended purpose of your model (e.g., to simulate daily flows at a very fine spatial resolution, water supply accounting, ecological flow assessment, water quality)?
5.	Please describe the model framework.
6.	What is the spatial extent of your model (e.g., Hydrologic Unit Code [HUC], river basin, etc.)? Do you have an attributed shapefile available that you could share with us?
7.	What is the spatial resolution of your model (e.g., grid cell, reach, basin, ecoregion) and approximate size of model units (e.g., ha, km ²)?
8.	What is the temporal resolution of your model (e.g., hourly, daily, monthly)?
9.	What is the time period represented by your model (e.g., start year and end year simulated)?
10.	What inputs does your model require (e.g., weather parameters, soils, land cover, water withdrawals, etc.), and how are they derived (calibrated, remote sensing, etc.)?
11.	What are the model outputs (e.g., flow, water quality, ecosystem response)?
12.	What elements of environmental change are represented by your model, if any (e.g., climate, land use change, withdrawals/flow regulation)?
13.	Please explain the procedure, criteria, and results of your model validation (e.g., specific U.S. Geological Survey gauges, other flow data)?
14.	What time scale was validated (e.g., mean annual, annual, seasonal, monthly, daily, hourly)?
15.	What fit statistics were used (e.g., bias, R ² , Nash-Sutcliffe Efficiency, etc.), and at what level was the model performance considered satisfactory?
16.	How can we use your model (i.e., Is it downloadable, proprietary, publicly available?)?
17.	May we contact you again with further questions/technical assistance if necessary?
18.	Can you recommend other professionals we should contact regarding hydrologic modeling, especially flow ecology/ecohydrology in the Southeast/Puerto Rico?
19.	Has your model ever been used in the Apalachicola-Chattahoochee-Flint (ACF) Basin? Is there any reason why your model would not be an appropriate choice to use in the ACF Basin, or, alternatively, is there any reason why your model would be an ideal choice to use in the ACF Basin?

Table 2.2—List of Federal and State agencies, academic institutions, and environmental consultants that were contacted for an inventory of existing hydrologic models

Organization ^a	Location	Type	Total solicited ^b	Total responses ^b
Alabama Department of Economic and Community Affairs, Office of Water Resources	Alabama	State	1	1
The University of Alabama in Huntsville, Department of Civil and Environmental Engineering	Alabama	University	1	0
Auburn University, Alabama Water Resources Research Institute	Alabama	University	1	0
Auburn University, Department of Biosystems Engineering	Alabama	University	1	0
Auburn University, School of Forestry and Wildlife Sciences	Alabama	University	1	0
The University of Alabama in Huntsville, Department of Atmospheric Science	Alabama	University	2	0
Arkansas Department of Environmental Quality, Water Division	Arkansas	State	2	0
U.S. Geological Survey, Arkansas Water Science Center	Arkansas	Federal	1	0
Purdue University, Department of Agricultural & Biological Engineering	Arkansas	University	1	1
Arkansas Cooperative Fish and Wildlife Research Unit	Arkansas	State	1	1
University of Arkansas, Division of Agriculture, Arkansas Water Resources Center	Arkansas	University	2	0
University of Arkansas, Department of Biological and Agricultural Engineering	Arkansas	University	2	0
University of Arkansas, Department of Crop, Soil, and Environmental Science	Arkansas	University	1	0
U.S. Geological Survey, Global Change Research Program	Colorado	Federal	1	2
University of Florida, Water Resources Research Center	Florida	University	2	0
U.S. Geological Survey, Caribbean-Florida Water Science Center	Florida	Federal	2	0
Georgia Tech, Georgia Water Resources Institute	Georgia	University	1	0
U.S. Geological Survey, Global Change Research Program	Georgia	Federal	1	1
U.S. Department of Agriculture Agricultural Research Service, Southeast Watershed Research	Georgia	Federal	1	0
U.S. Geological Survey, South Atlantic Water Science Center	Georgia	Federal	1	0
University of Notre Dame, Department of Biological Sciences	Indiana	University	1	1
U.S. Geological Survey, Ohio-Kentucky-Indiana Water Science Center	Kentucky	Federal	2	2
Kentucky Energy and Environment Cabinet, Department for Environmental Protection, Division of Water	Kentucky	State	3	0
University of Kentucky, Kentucky Water Resources Research Institute	Kentucky	University	2	0
U.S. Geological Survey, Lower Mississippi-Gulf Water Science Center	Louisiana	Federal	2	0
Louisiana State University, Louisiana Water Resources Research Institute	Louisiana	University	3	0
Mississippi State University, Mississippi Water Resources Research Institute	Mississippi	University	2	0
Mississippi State University, Department of Civil and Environmental Engineering	Mississippi	University	1	1
U.S. Geological Survey, Lower Mississippi-Gulf Water Science Center	Mississippi	Federal	1	0
Missouri Department of Natural Resources, Water Resources Center	Missouri	State	1	0
U.S. Geological Survey, Central Midwest Water Science Center	Missouri	Federal	3	0
University of Missouri, Missouri Water Resources Research Center	Missouri	University	1	0
U.S. Geological Survey, South Atlantic Water Science Center	North Carolina	Federal	1	0
North Carolina Department of Environmental Quality, Division of Water Resources	North Carolina	State	1	0
North Carolina State University, Department of Civil, Construction, and Environmental Engineering	North Carolina	University	2	0
Water Resources Research Institute of the University of North Carolina System	North Carolina	University	3	0

(continued on next page)

Table 2.2 (continued)—List of Federal and State agencies, academic institutions, and environmental consultants that were contacted for an inventory of existing hydrologic models

Organization ^a	Location	Type	Total solicited ^b	Total responses ^b
Duke University, Nicholas School of the Environment	North Carolina	University	1	1
U.S. Department of Agriculture Forest Service, Eastern Forest Environmental Threat Assessment Center	North Carolina	Federal	1	1
Tetra Tech	North Carolina	Consultant	1	2
Research Triangle Institute	North Carolina	Consultant	1	1
North Carolina State University, Department of Biological Sciences	North Carolina	University	1	0
Oklahoma Water Resources Board	Oklahoma	State	2	1
Oklahoma State University, Oklahoma Water Resources Center	Oklahoma	University	2	0
Oklahoma State University, Department of Natural Resource Ecology and Management	Oklahoma	University	1	0
U.S. Geological Survey, Oklahoma Water Science Center	Oklahoma	Federal	1	0
South Carolina Department of Natural Resources, Hydrology Section	South Carolina	State	1	0
U.S. Geological Survey, South Atlantic Water Science Center	South Carolina	Federal	1	1
Clemson University, South Carolina Water Resources Center	South Carolina	University	3	0
University of South Carolina, School of the Earth, Ocean and Environment	South Carolina	University	1	1
Tennessee Department of Environment & Conservation, Division of Water Resources	Tennessee	State	1	0
U.S. Geological Survey, Lower Mississippi-Gulf Water Science Center	Tennessee	Federal	1	1
The University of Tennessee, Knoxville, Tennessee Water Resources Research Center	Tennessee	University	1	0
Tennessee Technical University, Center for the Management, Utilization and Protection of Water Resources	Tennessee	University	1	0
Tennessee Technical University, Department of Civil & Environmental Engineering	Tennessee	University	1	0
Texas Commission on Environmental Quality, Office of Water, Water Availability Division	Texas	State	1	0
U.S. Geological Survey, Texas Water Science Center	Texas	Federal	5	1
Texas Water Resources Institute	Texas	University	2	0
U.S. Army Corps of Engineers, System-Wide Water Resources Program	Texas	Federal	1	0
Texas A&M University, Spatial Sciences Laboratory	Texas	University	1	0
Texas A&M University, Department of Civil Engineering, Environmental and Water Resources Engineering Division	Texas	University	1	0
U.S. Geological Survey, Virginia and West Virginia Water Science Center	Virginia	Federal	2	1
Virginia Tech, Virginia Water Resources Research Center	Virginia	University	2	0
West Virginia Department of Environmental Protection, Division of Water and Waste Management	West Virginia	State	1	0
U.S. Geological Survey, Virginia and West Virginia Water Science Center	West Virginia	Federal	2	1

^aOrganizations that were successfully contacted were asked to provide answers to a simple questionnaire (see table 2.1) regarding their hydrologic modeling efforts.

^bTotal solicited = the number of individuals solicited within each organization; Total responses = the number of modeling efforts described by those individuals who were successfully contacted within each organization. Where total responses are greater than the total solicited, there was more than one modeling effort described by one or more of the individuals contacted in that organization.

Table 2.3—Summary of survey responses and a description of the general purpose of flow models used in Southeastern United States and Puerto Rico modeling studies

Organization	Model type	Location of basins simulated																Use
		AL	AR	FL	GA	KY	LA	MS	MO	NC	OK	SC	TN	TX	VA	WV	PR	
USGS Ohio-Kentucky-Indiana Water Science Center	Rainfall-runoff (TOPMODEL)				X													Assess climate change effects on streamflow.
USGS Ohio-Kentucky-Indiana Water Science Center	Rainfall-runoff (TOPMODEL)				X													Provide historic and baseline streamflow hydrographs for several USGS gauge locations in the Apalachicola-Chattahoochee-Flint (ACF) Basin.
Mississippi State University, Department of Civil and Environmental Engineering	Rainfall-runoff (HSPF)	X						X								X		Hydrological assessment of listed watersheds
USGS Lower Mississippi-Gulf Water Science Center	Rainfall-runoff (PRMS)	X			X								X					Estimate flow at ungauged tributaries.
USGS Lower Mississippi-Gulf Water Science Center	Statistical (regional linear multivariate regression)									X			X		X	X		Predict ungauged stream characteristics; employ predictions to determine their effect on documented fish communities.
Arkansas Cooperative Fish & Wildlife Research Unit	Statistical (decision trees and random forest models)		X						X		X							Impacts on fish and invertebrates
USGS Virginia and West Virginia Water Science Center	Rainfall-runoff (HSPF)														X			Determine flow statistics under climate scenarios. Identify areas where mussel thresholds will be crossed under climate change.
USGS Virginia and West Virginia Water Science Center	Rainfall-runoff (HSPF)															X		Cumulative Hydrologic Impact Assessment for coal mining.
Duke University, Nicholas School of the Environment	Rainfall-runoff (GR4J)									X								Effect of doubling CO ₂ on streamflow
USGS South Atlantic Water Science Center	Statistical (Calibrated Artificial Neural Network)									X		X						Simulate salinity levels for water utilities' relicensing purposes.
USGS Texas Water Science Center ^a	Rainfall-runoff (RRFLOW)																	Represent changes in response to climate but could also be set up to simulate the effects of groundwater withdrawals.
University of South Carolina, School of the Earth, Ocean and Environment	Rainfall-runoff (HSPF)									X		X						Climate, land use, and water management effects on future streamflow and water quality

(continued on next page)

Table 2.3 (continued)—Summary of survey responses and a description of the general purpose of flow models used in Southeastern United States and Puerto Rico modeling studies

Organization	Model type	Location of basins simulated																Use
		AL	AR	FL	GA	KY	LA	MS	MO	NC	OK	SC	TN	TX	VA	WV	PR	
Oklahoma Water Resources Board	Statistical (CRAM)										X							Administration of water rights; diversion of surface water and estimates if demands are met
University of Notre Dame, Department of Biological Sciences ^a	Rainfall-runoff (SWAT)																	Both climate and land use change scenarios can be represented.
Purdue University, Department of Agricultural & Biological Engineering	Rainfall-runoff (SWAT)		X															Quantify current and future ecosystem services and examine changes as a result of growing demand for biofuels.
USDA Forest Service, Eastern Forest Environmental Threat Assessment Center	Rainfall-runoff (WaSSI)	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Climate, land use, population growth
Tetra Tech	Rainfall-runoff (HSPF & SWAT)	X		X	X		X			X				X				Assess the sensitivity of streamflow, nutrient, and sediment loads to climate change and urban development.
Research Triangle Institute	Rainfall-runoff (GWLf)	X		X	X					X		X			X			Hydrologic foundation development, resiliency, ecological flow development, and climate and land use change analyses
USGS Global Change Research Program (Colorado)	Rainfall-runoff (PRMS & MWBM)	X		X	X			X		X		X	X		X			Provide daily or monthly time series of streamflows at several sites across the Southeast as part of a USGS National Water Census study.
USGS Global Change Research Program (Georgia)	Rainfall-runoff (PRMS)	X		X	X													Understand the effect of climate change on ecosystem responses as part of the USGS Southeast Regional Assessment Project.

^a Respondent was model developer; their response did not describe application of the model.

CRAM = a proprietary network flow model used to simulate water resources systems; GR4J = a lumped bucket-type daily rainfall-runoff model; GWLF = Generalized Watershed Loading Function; HSPF = Hydrological Simulation Program-Fortran; MWBM = Monthly Water Balance Model; PRMS = Precipitation-Runoff Modeling System; RRAWFLOW = Rainfall-Response Aquifer and Watershed Flow Model; SWAT = Soil and Water Assessment Tool; TOPMODEL = physically based, semi-distributed topographical watershed model; USDA = U.S. Department of Agriculture; USGS = U.S. Geological Survey; WaSSI = Water Supply Stress Index model.

CONCLUSIONS

Here we created an inventory of existing hydrologic modeling efforts in the SEUS and PR. The 22 individuals interviewed developed and used hydrologic models to answer broad questions regarding the impacts of environmental change on water resources. With the rapid pace of computing technology and growth of modeling

approaches, as well as changing threats to watersheds across the landscape, it is expected that this model inventory will continue to evolve and thus represents a snapshot of approaches and knowledge gaps in hydrologic modeling for flow-ecology science and environmental change assessment studies across the SEUS and PR.

CHAPTER 3

Evaluation and Comparison of Hydrologic Model Performance in Predicting Observed Streamflows in the Southeastern United States

INTRODUCTION

Hydrologic models are commonly used to develop a hydrologic foundation (Poff and others 2010) because they have the ability to simulate monthly, daily, or sub-daily streamflow under baseline conditions and an infinite number of scenarios of flow alteration. Available hydrologic models vary in their levels of complexity, temporal and spatial resolution, and required level of calibration. Detailed and highly parameterized fine-resolution models (e.g., distributed physically based watershed and rainfall-runoff models) are well suited for smaller domains but can be computationally expensive and difficult to parameterize at a large scale. Easily parameterized models (e.g., lumped regional models) are useful for assessing broad implications of streamflow alteration at a large scale and identifying potential water-limited areas (or “hot spots”) but may have difficulty resolving unique sub-watershed physical processes and anthropogenic effects. Regardless of the hydrologic model used, the model must be able to reasonably replicate streamflow observations and ecologically relevant flow metrics (ERFMs) describing the five primary components of the flow regime (i.e., magnitude, frequency, duration, timing, and rate of change) under historical and current conditions across points of interest for regulation. The model must also predict changes in these metrics as a result of changes in climate, land use, flow regulation, and water withdrawals. Error (i.e., uncertainty or bias) in hydrologic model prediction of streamflow and ecological model prediction of ecosystem response to changes in flow (e.g., development of flow-ecology response models) is compounding; therefore, error in hydrologic model prediction of streamflow is often carried through the analysis and should be quantified and reported to reduce the probability of spurious relations and misinterpretation of modeling outcomes.

Given the number of choices of hydrologic models for water supply and environmental flow studies (see chap. 2), it would be useful for resource managers to have some sense of the relative error in streamflow predictions among commonly used hydrologic models in terms of classical fit statistics of streamflow observations (e.g.,

bias, Nash-Sutcliffe Efficiency [NSE]) and ERFMs. Unfortunately, the determination as to which model is best suited for answering a particular ecological question or even whether one model is better suited for a specific region or for a specific portion of the flow regime (e.g., low flows) is hampered by a lack of comprehensive model comparison studies (Knight and others 2012). In addition to the type of hydrologic model, model inputs (e.g., climate, soils, land cover, etc.), calibration strategy, and the experience of the modeler will influence the capacity of a given hydrologic model to predict observed streamflow.

The aim of this study was to address gaps in our understanding of differences among hydrologic models when applied to 195 U.S. Geological Survey (USGS) continuous record gauging stations in the Southeastern United States (SEUS). We did not evaluate model applications in Puerto Rico (PR) because, at the time of this study, none of the models were sufficiently developed to provide streamflow predictions at gauged locations in PR. Since the completion of this work, the WaSSI model evaluated here was parameterized to predict monthly streamflow in PR (Cohen and others 2017, Zhang and others 2018). It was not the intent of this study to identify any specific model that is better suited for streamflow prediction over another because such differences are as likely to be related to model calibration strategy, experience, and personal preference as they are to differences in model structure. Rather, the overarching goal of this investigation was to quantify and compare the magnitude and investigate the potential causes of error associated with predicted streamflows from seven hydrologic models of varying complexity and calibration strategy by computing classical hydrologic model fit statistics (e.g., mean bias, coefficient of determination [R^2], root mean squared error [RMSE], and NSE) and bias in the prediction of ERFMs. In addition, we tested the hypotheses that (1) regional-scale hydrologic models would, in general, have poorer predictive capacity and higher levels of uncertainty than fine-scale models; and (2) models with higher levels of calibration would perform better than those with less calibration.

METHODS

Model Comparison Workshop

A model comparison workshop was held on February 12, 2013 in the Department of Forestry and Environmental Resources Jordan Hall at North Carolina State University. Workshop attendees (table 3.1; fig. 3.1) included a subset of the developers presented in the model inventory (chap. 2). The workshop included an overview of the project, a statement from Adam Terando (U.S. Department of the Interior Southeast Climate Adaptation Science Center [SCASC]) providing an overview of the ecohydrology research priority and relevance to the SCASC mission, an overview of the National Water Census model comparison study by Julie Kiang (USGS Office of Surface Water), descriptions of modeling work by all modelers, presentation of statistical comparisons

of predicted streamflow to observations at USGS gauges, and a discussion comparing and contrasting modeling approaches and how they relate to the ability to predict observed streamflow.

Model Descriptions

Specific models discussed and compared in the workshop were the Hydrological Simulation Program-Fortran (HSPF); the USGS Monthly Water Balance Model (MWBm); two parameterizations of the USGS Precipitation-Runoff Modeling System (PRMS) model; the Soil and Water Assessment Tool (SWAT); three parameterizations of the Water Availability Tool for Environmental Resources (WATER), based on the USGS TOPMODEL (a physically based, semi-distributed topographical watershed model); the Generalized

Table 3.1 — Model comparison workshop attendees, the organizations they represent, and the hydrologic models used

Attendee	Organization	Hydrologic model(s)
Jon Butcher	Tetra Tech, Research Triangle Park, NC	SWAT, HSPF
Peter Caldwell ^a	U.S. Department of Agriculture Forest Service, Eastern Forest Environmental Threat Assessment Center, Raleigh, NC	WaSSI
Michele Eddy	Research Triangle Institute, Research Triangle Park, NC	WaterFALL [®] (employs updated version of GWLF)
Lauren Hay	U.S. Geological Survey, Global Change Research Program, Lakewood, CO	PRMS, MWBM
Ernie Hain ^{a, b}	North Carolina State University, Department of Forestry and Environmental Resources, Raleigh, NC	—
Jonathan Kennen ^{a, b}	U.S. Geological Survey, National Water Census, Lawrenceville, NJ	—
Julie Kiang	U.S. Geological Survey, Water Mission Area, Analysis and Prediction Branch, Reston, VA	—
Jacob LaFontaine	U.S. Geological Survey, Global Change Research Program, Atlanta, GA	PRMS
Steven McNulty ^{a, b}	U.S. Department of Agriculture Forest Service, Eastern Forest Environmental Threat Assessment Center, Raleigh, NC	—
Stacy Nelson ^{a, b}	North Carolina State University, Department of Forestry and Environmental Resources, Raleigh, NC	—
Catalina Segura ^b	North Carolina State University, Department of Marine, Earth, and Atmospheric Sciences, Raleigh, NC	—
Timothy Shortley ^{a, b}	North Carolina State University, Department of Forestry and Environmental Resources, Raleigh, NC	—
Ge Sun ^a	U.S. Department of Agriculture Forest Service, Eastern Forest Environmental Threat Assessment Center, Raleigh, NC	WaSSI
Tanja Williamson	U.S. Geological Survey, Ohio-Kentucky-Indiana Water Science Center, currently in Lawrenceville, NJ	WATER (based on TOPMODEL)

^a Project team member.

^b Workshop attendees shown without an associated hydrologic model were project team members and/or contributors who did not provide model outputs for the comparison study.

GWLF = Generalized Watershed Loading Function; HSPF = Hydrological Simulation Program-Fortran; MWBM = Monthly Water Balance Model; PRMS = Precipitation-Runoff Modeling System; SWAT = Soil and Water Assessment Tool; TOPMODEL = physically based, semi-distributed topographical watershed model; WaSSI = Water Supply Stress Index model; WATER = Water Availability Tool for Environmental Resources; WaterFALL[®] = Watershed Flow and Allocation modeling system using NHDPlus.



Figure 3.1—The model comparison workshop was a daylong event hosted by North Carolina State University. This workshop allowed hydrologic modelers from multiple organizations across the SEUS to meet in a single location and discuss similarities and differences in modeling approaches, input data sources, calibration strategies, and model performance. (Photo by Ge Sun, USDA Forest Service)

Watershed Loading Function (GWLF)-based WaterFALL[®] model developed by Research Triangle Institute (RTI); and the U.S. Department of Agriculture (USDA) Forest Service Water Supply Stress Index (WaSSI) model (table 3.2). The MWBM and WaSSI models are regional, large-scale monthly streamflow models, while HSPF, PRMS, SWAT, WATER, and WaterFALL[®] are more complex highly parameterized, fine-scale daily or hourly streamflow models. All of the models evaluated in this study were developed by different organizations, for different purposes, and calibrated to different degrees using different objective functions as described below.

HSPF and SWAT

Both the HSPF and SWAT models used in this study were implemented by Tetra Tech as part of a larger study to characterize the sensitivity of streamflow, nutrient loading, and sediment loading to a range of potential mid-21st century climate futures in 20 large U.S. drainage basins (Johnson and others 2012, USEPA 2013). Model descriptions and information pertinent to this application are detailed below.

HSPF—The HSPF (Bicknell and others 2001, 2005) is a hydrology and water quality model commonly used for determination of Total Maximum Daily Loads to receiving

waters in response to the Clean Water Act. HSPF is a well-documented watershed model that computes the water balance based on the Stanford Watershed Model (Crawford and Linsley 1966) in multiple surface and subsurface layers at an hourly time step. The water balance is simulated based on Philip's infiltration (Bicknell and others 2001, 2005) coupled with multiple surface and subsurface stores (interception storage, surface storage, upper zone soil storage, lower zone soil storage, active groundwater, and inactive [deep] groundwater). Individual land units within a sub-basin are represented using a hydrologic response unit (HRU) approach that combines an overlay of land cover, soil, and slope characteristics. The stream network links the surface runoff and groundwater flow contributions from each of the HRUs and routes them through water bodies. The stream model includes precipitation (PPT) and evaporation from the water surfaces as well as streamflow contributions from the watershed, tributaries, and upstream stream reaches.

SWAT—SWAT was developed to simulate the effects of land management practices on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land use, and management conditions over long periods of time (Neitsch and others 2005). SWAT requires data inputs for weather, soils,

Table 3.2—General summary of model attributes

Model	Time step	Spatial resolution	Withdrawals, flow regulation simulated	Land cover input	Potential evapotranspiration method	Climate input
HSPF	hourly	HUC-10 (~410 km ²)	yes	2001 NLCD (Homer and others 2007)	Penman-Monteith (Monteith 1965, Jensen and others 1990)	Station observations (USEPA 2008)
MWBM	monthly	Aggregated NHDPlus catchments (~78 km ²)	no	N/A	Hamon (Hamon 1963)	PRISM (PRISM Climate Group 2013)
PRMS-SERAP	daily	HRU (~200 km ²)	no	2001 NLCD (Homer and others 2007)	Jensen-Haise (Jensen and Haise 1963)	Maurer (Maurer and others 2002)
PRMS-DAYMET	daily	Aggregated NHDPlus catchments (~78 km ²)	no	2001 NLCD (Homer and others 2007)	Jensen-Haise (Jensen and Haise 1963)	DAYMET (Thornton and others 2013)
SWAT	daily	HUC-10 (~410 km ²)	yes	2001 NLCD (Homer and others 2007)	Penman-Monteith (Monteith 1965, Jensen and others 1990)	Station observations (USEPA 2008)
WATER IDW 1992	daily	10 m x 10 m	no	1992 NLCD (Volgelmann and others 2001)	Hamon (Hamon 1963)	IDW (Hay and others 2002)
WATER IDW 2006	daily	10 m x 10 m	no	2006 NLCD (Fry and others 2011)	Hamon (Hamon 1963)	IDW (Hay and others 2002)
WATER NR 2006	daily	10 m x 10 m	no	2006 NLCD (Fry and others 2011)	Hamon (Hamon 1963)	NEXRAD
WaterFALL®	daily	NHDPlus catchment (~1.0 km ²)	no	ca. 1970s USGS GIRAS (Price and others 2006)	Hamon (Hamon 1963)	USDA (Di Luzio and others 2008)
WaSSI	monthly	HUC-12 (~80 km ²)	no	2006 NLCD (Fry and others 2011)	Function of leaf area, PPT, Hamon (Sun and others 2011b)	PRISM (PRISM Climate Group 2013)

DAYMET = Daily Meteorological Data; GIRAS = Geographic Information Retrieval and Analysis System; HRU = Hydrologic Response Unit; HSPF = Hydrological Simulation Program-Fortran; HUC = Hydrologic Unit Code; IDW = Inverse Distance Weighted; MWBM = Monthly Water Balance Model; NEXRAD = Next-Generation Radar; NHD = National Hydrography Dataset; NLCD = National Land Cover Database; NR = Next-Generation Radar; PPT = precipitation; PRISM = Parameter-elevation Relationships on Independent Slopes Model; PRMS = Precipitation-Runoff Modeling System; SERAP = Southeast Regional Assessment Project; SWAT = Soil and Water Assessment Tool; USDA = U.S. Department of Agriculture; WaSSI = Water Supply Stress Index model; WATER = Water Availability Tool for Environmental Resources; WaterFALL® = Watershed Flow and Allocation modeling system using NHDPlus.

topography, vegetation, and land use to model water and sediment movement, nutrient cycling, and numerous other watershed processes. SWAT (as implemented here) uses the curve number approach (USDA Soil Conservation Service 1972) to estimate surface runoff and then completes the water balance through simulation of subsurface flows, evapotranspiration (ET), soil storages, and deep seepage losses at the daily time step. The curve number is estimated as a function of land use, cover, condition, hydrologic soil group, and antecedent soil moisture.

HSPF and SWAT for this application—For both models, the 20 larger watersheds were divided into a series of sub-basins at approximately the Hydrologic Unit Code (HUC) 10-digit scale, representing the drainage areas that contribute to each of the stream reaches. Both the HSPF and SWAT models used the 2001 National Land Cover Database (NLCD) (Homer and others 2007) to characterize the land surface. For HSPF, soils are distinguished on the basis of hydrologic soil group (HSG) as defined in the State Soil Geographic (STATSGO) database (USDA NRCS 2012) soil coverages. The HRU definitions for SWAT in this application use the same land cover as HSPF but distinguish soils based on STATSGO's dominant soil

classification, not just HSG. Withdrawals were included if they resulted in a modification of flow at downstream gauges on the order of 10 percent or more. Time series of observed PPT and air temperature (TEMP; hourly for HSPF, daily for SWAT) from 37 weather stations in the Apalachicola-Chattahoochee-Flint (ACF) Basin were obtained from the 2006 BASINS 4 Meteorological Database (USEPA 2008). Potential evapotranspiration (PET) for both HSPF and SWAT was computed using the Penman-Monteith energy balance method (Jensen and others 1990, Monteith 1965) using solar radiation, wind movement, cloud cover, and relative humidity estimated using the SWAT weather generator. A full energy balance approach was used because the focus of the study is on evaluating potential response to future climates, in which the relations between different energy inputs may change, even though a better calibration fit to current climate conditions can often be obtained using simpler temperature-based approaches when the energy inputs are subject to uncertainty.

The calibration objectives for both HSPF and SWAT were to achieve error statistics for total streamflow volume, seasonal streamflow volume, and high and low streamflow within recommended ranges (Donigan 2000, Lumb and others 1994) while also maximizing the NSE (Nash and Sutcliffe 1970). Because the objectives of this application focused at the large basin scale, calibration was undertaken only at the HUC 8-digit and larger watershed scale. For this application of HSPF, four model parameters were the primary focus during model calibration to improve model fit for hydrology: INFILT (index to mean soil infiltration rate), AGWRC (groundwater recession rate), LZSN (lower zone nominal soil moisture storage), and BASETP (ET by riparian vegetation). For SWAT, 11 model parameters were adjusted during model calibration to improve model fit in this application: curve number; SECO (soil evaporation compensation factor); SURLAG (surface runoff lag coefficient); groundwater “revap” rates; baseflow factor; GW_DELAY (groundwater delay time); GWQMN (threshold depth of water in the shallow aquifer required for return flow to occur); RevapMN (threshold depth of water in the shallow aquifer required for “revap” or percolation to the deep aquifer to occur); CANMAX (maximum canopy storage); Manning’s “n” value for overland flow, main channels, and tributary channels; and Sol_AWC (available water capacity of the soil layer [mm water/mm of soil]).

PRMS-SERAP and PRMS-DAYMET

Two applications of the USGS PRMS were evaluated in this study: (1) a PRMS model developed for the USGS Southeast Regional Assessment Project (PRMS-SERAP), and (2) a PRMS model developed for the USGS National

Water Census using the DAYMET daily climate input data provided by the Oak Ridge National Laboratory (PRMS-DAYMET [Daily Meteorological Data]). The PRMS (Leavesley and others 1983, Markstrom and others 2008) is a deterministic, distributed-parameter, physical-process-based hydrologic modeling system. The model simulates daily land-surface hydrologic processes including ET by the Jensen-Haise radiation method (Jensen and Haise 1963), runoff, infiltration, and interflow in HRUs by balancing energy and mass budgets of the plant canopy, snowpack, and soil zone on the basis of distributed climate information (TEMP, PPT, and solar radiation). PRMS requires the input of daily maximum and minimum air TEMP and daily PPT time-series data.

PRMS-SERAP—The PRMS-SERAP model was developed to provide integrated science that helps resource managers understand the effect of climate change on a range of ecosystem responses in the ACF Basin (LaFontaine and others 2013). For this study, daily climate inputs were developed for the PRMS-SERAP model using a 1/8-degree gridded TEMP and PPT dataset for 1950–1999 (Maurer and others 2002). Withdrawals and flow regulation were considered during model calibration in areas where anthropogenic effects were substantial, mostly in the form of irrigation withdrawals (see Wen and Zhang 2009 for details) and releases from U.S. Army Corps of Engineers projects. These withdrawals and regulations were then removed in the final model runs to simulate unaltered flow volumes.

PRMS-DAYMET—The PRMS-DAYMET model was developed to provide flow estimates at several sites across the Southeast as part of the USGS National Water Census model comparison study. The HRUs for the PRMS-DAYMET model were developed by aggregating catchments of the medium-resolution National Hydrography Dataset (NHDPlus) to an average size of 78 km². The daily climate data for PRMS-DAYMET were derived from the 1- x 1-km gridded DAYMET daily TEMP and PPT dataset for 1980–2008 (Thornton and others 2013). No anthropogenic withdrawals were included.

For the PRMS applications in this study, soil-zone, subsurface, and groundwater-reservoir parameters were computed using the Soil Survey Geographic database (SSURGO) (https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053627), maps of near-surface permeability (Gleeson and others 2011), and hydrographs of USGS stream gauges. Land cover characteristics, such as impervious area, canopy density, and land cover type, were obtained from the 2001 NLCD (Homer and others 2007) and summarized per HRU. For land cover type, each HRU was assigned one of four

vegetation cover classes (bare soil, grasses, shrubs, trees) based on the dominant land cover type, defined as having the largest percentage of HRU area.

An automated parameter estimation procedure (Duan and others 1994) was combined with a geographically nested approach to calibrate the PRMS models in two phases with a total of four steps using the Luca software (Hay and Umemoto 2006, Hay and others 2006). The first phase of calibration involved matching simulated and measured solar radiation (three model parameters) and PET (one model parameter), and the second phase of calibration involved matching simulated and measured streamflow volumes and timing (20 model parameters). The objective function in Phase I of model calibration was to minimize the absolute difference between predicted and observed monthly solar radiation and PET. The objective function in Phase II of model calibration depended on the application of PRMS. For PRMS-SERAP, the objective function in Phase II of model calibration was to minimize the normalized root mean squared error (RMSE) of flow volumes on an annual, monthly, and mean monthly basis and to minimize the normalized RMSE of daily flow timing using a 3-day moving average. For PRMS-DAYMET, Phase II was expanded to four steps with the objective functions targeted at minimizing the normalized RMSE at a daily time step instead of the 3-day moving average of the PRMS-SERAP model. The four steps of calibration for PRMS-DAYMET included (1) matching annual, monthly, and mean-monthly flow volumes; (2) matching all daily streamflow values; (3) matching high-flow days only; and (4) matching low-flow days only.

WATER

WATER, developed within the USGS Center for Applied Hydrologic Solutions, is a spatially distributed, object-oriented, decision-support system that combines the expertise of numerous hydrologists, pedologists, computer scientists, and other discipline experts into a user-friendly computer application for managing water resources. WATER is based on the TOPMODEL hydrologic model and incorporates physiographic data that quantitatively describe topography and soil water storage. TOPMODEL, which simulates the variable-source-area concept of streamflow generation (Wolock 1993), is well documented (Beven and Kirkby 1979) and has been successfully applied in many environments (Beaujouan and others 2001, Boyer and others 1996, Engel and others 2002). There are three fundamental assumptions associated with TOPMODEL: (1) steady-state recharge to the groundwater; (2) hydraulic gradient of the water table that approximates the surface slope; and (3) a transmissivity profile that decreases exponentially with depth. The foundation of TOPMODEL is built on the assumption that the land surface is pervious to rainfall

and that water movement is a function of topography. Separate calculations were added from the USDA Natural Resources Conservation Service (NRCS) TR-55 method (USDA NRCS 1986) to simulate the disposition of water for impervious areas of the basin using runoff curve numbers specific to pavement. This simulated runoff from impervious-surface areas was then input to the TOPMODEL mass-balance equation at the beginning of each time step to partition runoff derived from pervious areas into its surface and subsurface components.

WATER as applied here was developed to provide historic and baseline streamflow hydrographs for several USGS gauge locations in the ACF Basin based on an approach developed for Kentucky (Williamson and others 2009, 2013) with a combination of the U.S. General Soil Map (STATSGO2) and the SSURGO. Land cover data from both the 1992 NLCD (Vogelmann and others 2001) and 2006 NLCD (Fry and others 2011) were used in model simulations. Both the National Weather Service River Forecast Centers Next-Generation Radar (NEXRAD, hereafter NR) and Inverse Distance Weighted (IDW; Hay and others 2002) climate inputs were used. Three combinations of land cover and climate inputs were evaluated in this study and are identified as WATER IDW 1992, WATER IDW 2006, and WATER NR 2006.

WATER was calibrated for six basins in the ACF Basin using a combination of manual calibration and the Parameter Estimation Tool (PEST) (Doherty 2008) on daily flows. For PEST, the weight of each observation was defined as

$$\omega = y_i \times \sigma^2$$

where

ω is the weight of an individual observation

y_i is an individual daily observation

σ^2 is the variability in error for an individual observation

If $y_i < \text{mean daily flow for the site}$, then $\omega = 0.1$; if $y_i > \text{mean daily flow for the site}$, then $\omega = 0.2$.

For days where PPT occurred, $\omega = 0$; flow on event days was given a zero weight because WATER uses a random distribution of daily PPT, so it is unlikely that the initial flow from a PPT event will be matched simply due to differences in how PPT was modeled versus how the event actually occurred. WATER was calibrated by adjusting rooting depth and a spatial coefficient that scales the topographic wetness index.

WaterFALL®

Research Triangle Institute's WaterFALL® modeling system employs an updated version of a well-established hydrologic model, the Generalized Water Loading Function (GWLF) (Haith and Shoemaker 1987, Haith and others 1992), that has been modified to (1) run on the U.S. Environmental Protection Agency's (USEPA) enhanced NHDPlus hydrologic network, (2) accept parameterization from national datasets, and (3) include the impacts of human alterations on streamflows. WaterFALL® utilizes the hydrologic simulation within GWLF for each catchment of the NHDPlus network in the watershed of interest and then accumulates and moves water downstream with an embedded time-lagged routing routine, providing a distributed hydrologic model across the NHDPlus. Parameterization of WaterFALL® occurs through the geoprocessing of national datasets for land cover, soils, and climate (mean daily TEMP and PPT) to each NHDPlus catchment. Each land cover class in a catchment is characterized by the predominant HSG and predominant percent sand, silt, and clay for the underlying soil forming an HRU for runoff calculation within the catchment. Mean TEMP and PPT are quantified by catchment. Additional basin-specific characteristics such as water uses may also be indexed to each catchment from local data sources.

Like SWAT and WATER, surface runoff in WaterFALL® is computed on a daily basis using the curve number method across each land cover type in a catchment (USDA Soil Conservation Service 1972). Discharge from shallow groundwater is computed using a lumped parameter catchment-level water balance for unsaturated and shallow saturated zones controlled by the available water capacity (AWC) of the unsaturated zone, a recession coefficient (RCoeff) providing the rate of release from the saturated zone to the stream channel, and a first-order approximation of infiltration losses to deep aquifer storage simulated using a seepage coefficient (SEEP). The seepage release constitutes a loss from the system, where the water is no longer available to reach the stream in the temporal context of daily rainfall-runoff modeling. Daily ET from the unsaturated zone is computed using a land use-based cover factor, and PET is computed using the Hamon temperature-based method (Hamon 1963). Three model parameters (AWC, RCoeff, and SEEP) are adjusted during an automated calibration process using a customized version of the PEST. Because of the physical basis of the AWC and RCoeff parameters, a priori values for the parameters are indexed to individual catchments within the WaterFALL® database, and a multiplier across the physically based values is adjusted during calibration. The SEEP parameter is set through calibration and consideration of local conditions.

The application of WaterFALL® used for this study was developed to create a hydrologic foundation for detailed assessment of human and climate effects on stream and river flows, including the effects of hydrologic alterations on aquatic habitats in the SEUS at the NHDPlus catchment scale (~1.0 km²) (Kendy and others 2011). For this study, climate inputs included daily PPT and TEMP from a 4- x 4-km national dataset obtained from the USDA (Di Luzio and others 2008), land cover was based on the baseline condition assessment represented by the USGS Geographic Information Retrieval and Analysis System (GIRAS) land cover (Price and others 2006), and soils data were obtained from SSURGO (https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053627). Although water system discharges and withdrawals were obtained from State databases on public and non-public systems for other scenarios in the SEUS study, the WaterFALL® model simulations contributing to this study were unaltered by humans. WaterFALL® was calibrated at several USGS gauge locations in the study area for periods in the 1970s, commensurate with the land use coverage used to simulate a less-altered baseline for the SEUS study. Although performance was validated with later periods, some differentiation from the other models is expected where the calibration period more closely matched the period of this study. The three model calibration parameters (AWC, RCoeff, and SEEP) were optimized to minimize the differences in log-transformed daily flows, giving equal weight to differences in streamflows at the low and high end of the hydrograph.

MWBM

The USGS MWBM (Hay and McCabe 2002, McCabe and Markstrom 2007, McCabe and Wolock 2011) is based on the monthly Thornthwaite water balance model (Thornthwaite 1948). PET is calculated from monthly TEMP using the Hamon equation (Hamon 1963). When PPT exceeds PET in a given month, actual ET is equal to PET. Water in excess of PET replenishes soil-moisture storage. When soil-moisture storage reaches field capacity during a given month, the excess water becomes surplus. In a given month, some percentage of the total surplus becomes runoff, and the remaining surplus is carried over to the following month. Like PRMS-DAYMET, the MWBM used in this study was developed to provide flow estimates at several sites across the Southeast as part of the USGS National Water Census model comparison study. The model was run on the same HRUs as were developed for the PRMS-DAYMET model and used PRISM (Parameter-elevation Relationships on Independent Slopes Model)-based monthly precipitation and TEMP estimates (PRISM Climate Group 2013). Four model parameters were adjusted during model calibration: PETfac (a PET

correction factor), RO_{fac} (percentage of the total surplus that becomes runoff), WHC (water holding capacity), and P_{bias} (monthly PPT bias). The calibration objective was to minimize normalized RMSE and bias using the same algorithms as the PRMS-SERAP and PRMS-DAYMET models.

WaSSI

The WaSSI model was developed by the Forest Service to assess the effect of climate change, land use change, and population growth on water supply stress, river flows, and aquatic ecosystems across the conterminous United States (Caldwell and others 2012, Sun and others 2011b). WaSSI has been successfully used in climate change assessments in the Eastern United States (Lockaby and others 2011, Marion and others 2013, Sun and others 2013, Tavernia and others 2013) and for examining the nexus of water and energy at the national scale (Averyt and others 2011, 2013). WaSSI is an integrated monthly water balance and flow routing model that simulates the full hydrologic cycle for each of 10 land cover classes at the 12-digit Hydrologic Unit Code (HUC) scale. The 10 land cover classes are aggregated from the 17 classes of the 2006 National Land Cover Database (NLCD) (Fry and others 2011). Infiltration, surface runoff, soil moisture, and baseflow processes for each HUC watershed land cover were computed using algorithms of the Sacramento Soil Moisture Accounting Model (SAC-SMA) (Burnash 1995, Burnash and others 1973). STATSGO databases (USDA NRCS 2012) were used to compute the 11 SAC-SMA soil input parameters (Koren and others 2003). Monthly ET was modeled with an empirical equation derived from multisite eddy covariance ET measurements (Sun and others 2011a, 2011b). Required data to estimate ET included monthly mean Moderate Resolution Imaging Spectroradiometer (MODIS) MOD15A2 leaf area index (LAI) (Zhao and others 2005), Hamon PET calculated as a function of TEMP and latitude (Hamon 1963), and PPT. This estimate of ET was then constrained by the soil water content computed by the SAC-SMA algorithm during extreme water-limited conditions. Monthly PPT and air TEMP inputs were based on PRISM estimates (PRISM Climate Group 2013). All water balance components were computed independently for each land cover class within each HUC watershed and accumulated to estimate the totals for the watershed. For the NLCD-based impervious cover fraction, storage and ET were assumed to be negligible, and thus all PPT falling on the impervious portion of a watershed for a given month was assumed to generate surface runoff in the same month and was routed directly to the watershed outlet. No anthropogenic water use was included, and the model was run using off-the-shelf input datasets without calibration.

Site Description and Observed Streamflow Sites

The study area included USGS streamflow gauges across eight States in the SEUS (fig. 3.2). Central to the study area is the ACF Basin which drains approximately 52,000 km² of Georgia, Alabama, and Florida. For over 2 decades, there have been periodic conflicts over water resources in the ACF Basin among Georgia, Alabama, and Florida and other stakeholders that depend on the river system for public supply, industry, power generation, and agriculture. As the region has grown and developed over the past 50 years, competition among all water users has become more pronounced, particularly during drought conditions (Seager and others 2009). As a result, the basin has been intensely studied over the last decade with multiple modeling efforts taking place to evaluate drought and environmental change effects on water supply and aquatic ecosystems (e.g., Alley and others 2013, Freeman and others 2013, Georgakakos and others 2010, LaFontaine and others 2013).

The gauges were selected because they had long records of continuous streamflow measurements, and, to our knowledge, there were no major dams, diversions, etc. that substantially altered the flow regime. While we attempted to limit this study to basins with minimally altered flow regimes, there could be unknown anthropogenic processes in the basins that are not accounted for in the models and could affect model predictive performance. Drainage areas of the 195 sites ranged from 14 to 44,548 km². The number of gauges and temporal extents varied among models (fig. 3.2, table 3.3), so model performance was not directly comparable across all gauges. However, a subset of gauges (table 3.4) were simulated by the HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL[®], MWBM, and WaSSI models (i.e., all models except the three parameterizations of WATER) from 1980–1999. Models were compared in two ways: first, by comparing all models across all gauges and time periods simulated irrespective of whether or not simulations were performed at the same sites (fig. 3.2, table 3.3), and second, by directly comparing model predictions at the subset of gauges simulated by HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL[®], MWBM, and WaSSI models (fig. 3.3, table 3.4).

The five gauges simulated by HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL[®], MWBM, and WaSSI models from 1980–1999 were all located in the ACF Basin (fig. 3.3) ranging in drainage area from 637 to 4792 km² with mean annual PPT ranging from 1282 mm to 1728 mm and mean annual TEMP ranging from 13.9 to 18.7 °C (table 3.4). Land cover ranged from mostly forested (site 1: Chattahoochee River near Cornelia, GA),

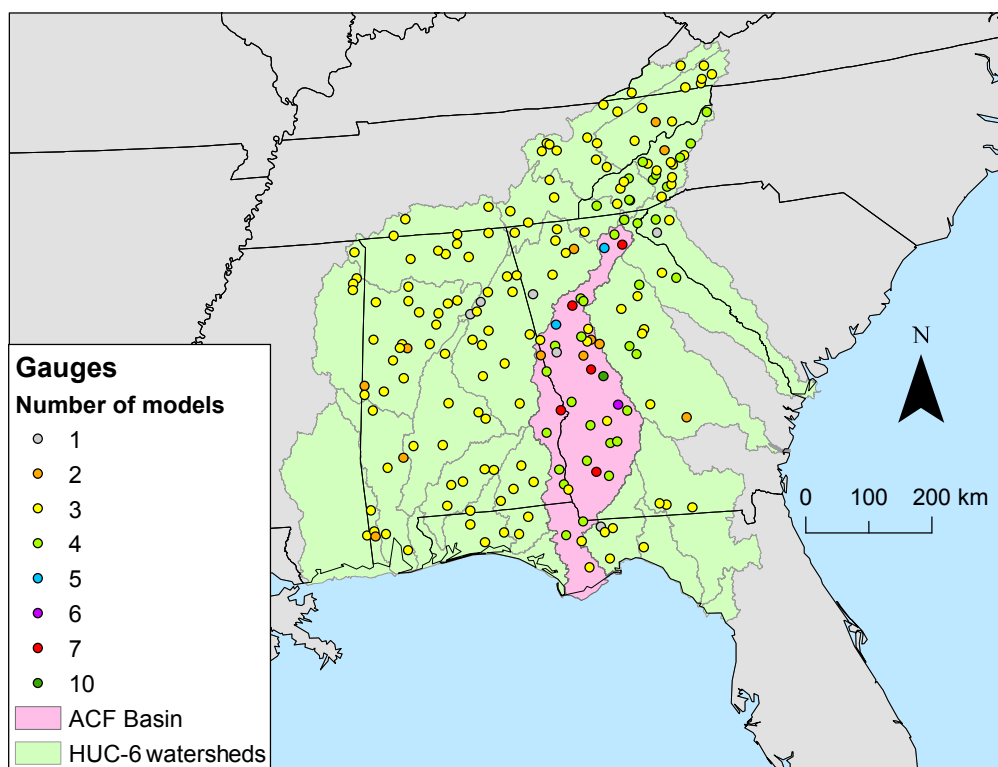


Figure 3.2—Spatial distribution of USGS streamflow gauges in the SEUS used to evaluate model performance in predicting observed streamflows. Colors of the gauge sites indicate the number of models that simulated streamflow for that site.

to highly urbanized (site 2: Sweetwater Creek near Austell, GA), to mixed agriculture and forest along the southern extent of the ACF Basin (site 5: Ichawaynochaway Creek at Milford, GA). The amount of impervious area ranged from 0.4 to 9.4 percent and was highly related to the amount of developed land in the basin ($R^2 = 0.986$).

Evaluation and Comparison of Error in Modeled Flows

In this study, we compared classical hydrologic model fit statistics among model applications, sites, and levels of calibration (1) over all sites and time periods simulated by each model and (2) over the five sites simulated by HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL®, MWBM, and WaSSI models from 1980–1999. Classical hydrologic model fit statistics were computed for each model and site at the monthly time step for all seven models and at the daily time step for hourly and daily models only. Fit statistics evaluated included RMSE, R^2 , bias in mean streamflow, and the NSE statistic (Nash and Sutcliffe 1970). The NSE can range from negative infinity to 1.0; the closer NSE is to 1.0, the better the model fit to observations. Negative values of NSE indicate that using the mean of the observations provides a better fit than the model. NSE values that are >0.50 , >0.65 , and >0.75 for prediction of monthly streamflow have been viewed

as indicative of satisfactory, good, and very good model performance, respectively (Moriassi and others 2007). Similarly, bias in mean streamflow within ± 25 , ± 15 , and ± 10 percent is indicative of satisfactory, good, and very good model performance, respectively (Moriassi and others 2007).

As discussed previously, models evaluated in this study were developed by different agencies, for different purposes, with different data inputs and spatial scales, and were calibrated using different objective functions. Some models were not calibrated at all, and some calibrated models were either specifically calibrated at these sites during model development or were calibrated for another streamflow gauge downstream. Some model calibration included adjusting PPT, solar radiation, and PET inputs. To examine the role that the level of model calibration plays in predictive performance, we define four levels of increasing calibration intensity to form a basis for comparison among models: calibration level A models are uncalibrated (i.e., WaSSI); calibration level B models are calibrated to a downstream gauge (i.e., some HSPF, SWAT, and WaterFALL® sites); calibration level C models are calibrated specifically for that site (i.e., some HSPF, SWAT, WATER, and WaterFALL® sites); and calibration level D models are calibrated specifically for that site,

Table 3.3—Summary of calibration level for gauges simulated by each model

Model	Number of gauges	Drainage area (km^2)			Time period	Number of gauges in calibration level ^a			
		Minimum	Maximum	Median		A	B	C	D
HSPF	12	2244	44 548	4274	10/1973–9/2003	0	3	9	0
PRMS-SERAP	27	92	44 548	834	10/1951–12/1999	0	0	0	27
PRMS-DAYMET	174	14	39 075	435	10/1980–9/2011	0	0	0	174
SWAT	12	2244	44 548	4274	10/1973–9/2003	0	3	9	0
WATER IDW 1992	3	262	4792	3160	1/1981–12/2008	0	0	3	0
WATER IDW 2006	9	23	7563	705	1/1981–12/2008	0	0	9	0
WATER NR 2006	9	23	7563	521	10/2001–12/2010	0	0	9	0
WaterFALL [®]	26	14	4792	254	1/1980–12/2006	0	2	24	0
MWBM	175	14	39 075	440	1/1980–12/2011	0	0	0	175
WaSSI	184	14	44 548	456	10/1980–9/2010	184	0	0	0

^a Calibration levels include: (A) uncalibrated, (B) calibrated to downstream gauge, (C) calibrated specifically for site, and (D) calibrated specifically for site with adjusted precipitation, solar radiation, and potential evapotranspiration (PET) inputs.

DAYMET = Daily Meteorological Data; HSPF = Hydrological Simulation Program-Fortran; IDW = inverse distance weighted; MWBM = Monthly Water Balance Model; NR = next generation radar; PRMS = Precipitation-Runoff Modeling System; SERAP = Southeast Regional Assessment Project; SWAT = Soil and Water Assessment Tool; WaSSI = Water Supply Stress Index model; WATER = Water Availability Tool for Environmental Resources; WaterFALL[®] = Watershed Flow and Allocation modeling system using NHDPlus.

Table 3.4—Descriptions^a of the five U.S. Geological Survey continuous record gauges simulated by HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL[®], MWBM, and WaSSI models (1980–1999)

Site number	1	2	3	4	5
Station ID	02331600	02337000	02342500	02347500	02353500
Station name	Chattahoochee River near Cornelia, GA	Sweetwater Creek near Austell, GA	Uchee Creek near Fort Mitchell, AL	Flint River at US 19, near Carsonville, GA	Ichawaynochaway Creek at Milford, GA
Drainage area (km^2)	816	637	834	4792	1606
Screening comments for alteration	Forested headwaters, mixed light agriculture/forest/suburban, many flood retention ponds on tributaries	Urban basin	Urban in headwaters of main tributary	Upstream urban	Proximate irrigated agriculture, many small ponds in headwaters, small towns on some tributaries
Developed	8.8%	39%	8.1%	13.9%	3.3%
Impervious	1.1%	9.4%	1.3%	3.6%	0.4%
Forested	72%	41%	52%	55%	39%
Agriculture	13%	11%	16%	16%	37%
Mean TEMP ($^{\circ}C$)	13.9	15.3	17.4	16.8	18.7
Mean PPT ($mm\ yr^{-1}$)	1728	1384	1320	1282	1330
Mean runoff ($mm\ yr^{-1}$)	615	497	448	411	426
Runoff coefficient	36%	36%	34%	32%	32%

^a Descriptive watershed data is from Falcone and others (2010) and Falcone (2011).

PPT = precipitation; TEMP = air temperature.

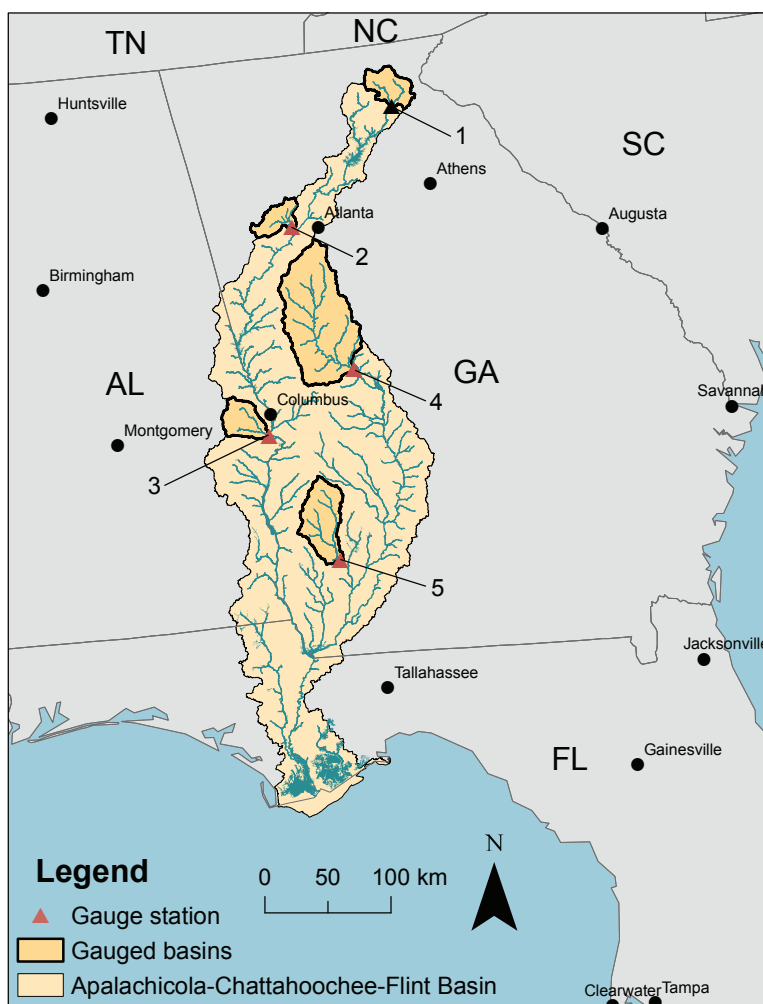


Figure 3.3—Map showing the location of the five USGS continuous record gauges and associated drainage basins in the Apalachicola-Chattahoochee-Flint Basin used to compare simulated flow predictions from the HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL®, MWBM, and WaSSI models (1980–1999).

and PPT, solar radiation, and PET inputs were adjusted as part of the calibration process to account for uncertainty in gridded climate estimates (i.e., PRMS models and MWBM) (tables 3.3 and 3.5).

We also evaluated differences between predicted and observed ERFMs across the five hourly and daily models over the five sites simulated by HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, and WaterFALL® models from 1980–1999. The monthly MWBM and WaSSI models were not evaluated for prediction of ERFMs because many of the ERFMs require a daily time step to be calculated. Predicted and observed daily mean flows were imported into the EflowStats package, an R version of the National Hydrologic Assessment Tool (NATHAT) (Henriksen and others 2006) developed by the USGS Center for Integrated Data Analytics and available on GitHub at <https://github.com/USGS-R/EflowStats>. This R package

was developed to assist water resource professionals with characterizing the five major components of the flow regime (i.e., magnitude, frequency, duration, timing, and rate of change) considered by many to be important in shaping ecological processes in streams (Henriksen and others 2006, Kennen and others 2007, Olden and Poff 2003). A total of 175 ERFMs were evaluated for this study. Scatterplots were used to examine data distributions and to detect potential outliers in the ERFMs; metrics with extreme outliers or with highly limited data ranges were removed from further consideration. A Spearman rank correlation matrix (SAS Institute Inc. 1989) on the reduced set of ERFMs was then examined to eliminate any remaining redundant variables with a Spearman's $\rho > 0.75$. In cases where two metrics accounting for similar aspects of the flow regime were highly collinear, selection was based on best professional judgment. This approach was highly parsimonious and permitted

Table 3.5—Level of model calibration by site for the five sites simulated by HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL®, MWBM, and WaSSI models from 1980–1999

Model	Number of parameters adjusted	Calibration objective function	Site	Level of calibration ^a
HSPF	4	Total, seasonal, high, and low streamflow within recommended ranges (Donigian 2000, Lumb and others 1994), maximize daily NSE	1	C
			2	B
			3	B
			4	B
			5	C
PRMS-SERAP	24	Minimize normalized RMSE of annual, monthly, and mean monthly flow volumes, and minimize normalized RMSE of daily flow timing using a 3-day moving average	1	D
			2	D
			3	D
			4	D ^b
			5	D
PRMS-DAYMET	24	Minimize normalized RMSE of annual, monthly, mean monthly, and daily flow volumes	1	D
			2	D
			3	D
			4	D
			5	D
SWAT	11	Total, seasonal, high, and low streamflow within recommended ranges (Donigian 2000, Lumb and others 1994), maximize daily NSE	1	C
			2	B
			3	B
			4	B
			5	C
WaterFALL®	3	Minimize bias in log-transformed daily flows	1	C
			2	C
			3	B
			4	C
			5	B
MWBM	4	Minimize normalized RMSE of annual, monthly, and mean monthly flow volumes	1	D
			2	D
			3	D
			4	D
			5	D
WaSSI	0	N/A	1	A
			2	A
			3	A
			4	A
			5	A

^a Calibration levels include: (A) uncalibrated, (B) calibrated to downstream gauge, (C) calibrated specifically for site, and (D) calibrated specifically for site with adjusted precipitation, solar radiation, and potential evapotranspiration (PET) inputs.

^b PRMS-SERAP was calibrated to a downstream gauge at site 4, but this calibration adjusted precipitation, solar radiation, and potential evapotranspiration inputs. For the purpose of comparison among calibration levels, PRMS-SERAP for this site was set at level D.

DAYMET = Daily Meteorological Data; HSPF = Hydrological Simulation Program-Fortran; MWBM = Monthly Water Balance Model; NSE = Nash-Sutcliffe Efficiency; PRMS = Precipitation-Runoff Modeling System; RMSE = root mean squared error; SERAP = Southeast Regional Assessment Project; SWAT = Soil and Water Assessment Tool; WaSSI = Water Supply Stress Index model; WaterFALL® = Watershed Flow and Allocation modeling system using NHDPlus.

the retention of important streamflow metrics which were highly interpretable and management oriented. It also helped avoid the possibility of establishing significant ($p < 0.05$) correlations among a large suite of hydrologic variables simply by chance and introducing interdependencies among multiple explanatory variables (King and others 2005, Van Sickle 2003). Bias in the resulting subset of ERFMs was quantified by computing the percent difference between the predicted and observed flow metric for each model and site. A hydrologic uncertainty of ± 30 percent (hereafter range of uncertainty) was used to aid in placing model prediction bias into context with inherent variability in streamflow and flow measurement (Murphy and others 2013).

All model streamflow predictions were compared to USGS flow observations at each site. After comparing classical fit statistics and prediction of ERFMs for each model, we explored differences in model structure, inputs, and calibration strategy that may explain differences in predictive performance. In addition, we examined differences in model input for monthly PPT and predicted ET, runoff, and soil moisture at site 4 (02347500, Flint River near Carsonville, GA; table 3.4; fig. 3.3) and the role these differences may play in the predicted water balance and model error for the HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL®, MWBM, and WaSSI models. PPT, ET, and runoff were directly comparable among all five models; however, soil moisture is represented differently in the flow models. To accommodate direct comparison, we standardized soil moisture predictions by dividing the monthly mean soil moisture by the maximum soil moisture storage for each model.

RESULTS

All Gauges Simulated by Each Model

Median model fit statistics over all gauges simulated by each model are shown in table 3.6. Note that the model fit statistics in table 3.6 are not directly comparable across models because the specific gauges and time periods simulated differed among models. In general, models captured the magnitude, variability of observed flows, and mean flow for the gauges and time periods they simulated with median absolute bias in mean flow < 6 percent across most models. The WATER IDW simulations tended to show high positive bias in many of the fit statistics. There was a tendency among some models to overestimate low flows. For example, the median bias in 10th percentile monthly flows was +17.1, +7.6, +37.0, +4.8, and +15.0 percent for HSPF, PRMS-SERAP, PRMS-DAYMET, WaterFALL®, and WaSSI, respectively. High flows were generally well predicted, with median bias in 90th percentile monthly flows within ± 4.3 percent among most models. Although bias in predicted low flows was greater

than that of high flows in relative terms (i.e., percent), there was little difference in low- and high-flow bias in absolute terms (i.e., cubic feet per second [cfs]). With the exception of WATER NR 2006, models generally under-predicted the coefficient of variation (CV) of observed flows regardless of the time scale. For example, the median bias in the CV in daily flows among daily time step models ranged from -2.6 percent (WaterFALL®) to -20.8 percent (PRMS-DAYMET), while that of WATER NR 2006 was +6.2 percent. Winter (December–February) and early spring (March–May) flows were generally well predicted, but late spring, summer, and early fall flows (June–November) were often over-predicted. This likely reflects the over-prediction of low flows because the lowest flows on an annual basis typically occur during the summer and early fall months. Model performance was satisfactory or better according to the Moriasi and others (2007) criteria for monthly NSE (> 0.50) and bias in mean flow (within ± 25 percent) at most of the gauges simulated by each model (fig. 3.4, table 3.7).

Comparison of Models for the Five Gauges Simulated by Select Models from 1980–1999

As mentioned previously, the number of gauges and temporal extents varied among models, so model performance was not directly comparable across all gauges. However, a subset of gauges (table 3.4) were simulated by the HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL®, MWBM, and WaSSI models (i.e., all models except the three parameterizations of WATER) from 1980–1999, allowing for direct comparisons among these models for the same sites and time periods. A complete summary of this comparison can be found in Caldwell and others (2015). In general, HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL®, MWBM, and WaSSI models captured the magnitude and variability of observed streamflows at the five study sites (table 3.8, figs. 3.5 and 3.6). The median bias in mean streamflow across sites by model ranged from -15.1 percent (WaterFALL®, site 5, calibration level B) to +15.4 percent (WaSSI, site 5, calibration level A), while median absolute bias across sites by model ranged from 2.5 percent (PRMS-DAYMET, site 1, calibration level D) to 15.4 percent (WaSSI, site 5, calibration level A). The median monthly NSE across all five study sites by model ranged from 0.64 (SWAT, site 2, calibration level B) to 0.87 (PRMS-SERAP, site 4, calibration level D). As expected, fit statistics for the daily models at the monthly time step were superior to the fit statistics at the daily time step for daily and sub-daily models. The median daily NSE across sites for the daily models (table 3.8) ranged from 0.37 (HSPF, site 5, calibration level C) to 0.80 (PRMS-SERAP, site 5, calibration level D). Using model performance criteria for bias and monthly NSE (Moriasi and others

Table 3.6—Median model fit statistics over all gauges simulated by each model

Statistic ^a	HSPF	PRMS-SERAP	PRMS-DAYMET	SWAT	WATER IDW 1992	WATER IDW 2006	WATER NR 2006	WaterFALL [®]	MWBM	WaSSI
Number of gauges	12	27	174	12	3	9	8	26	175	184
Calibration level ^b	B, C	D	D	B, C	C	C	C	B, C	D	A
Bias mean flow	5.9%	2.8%	3.8%	3.2%	38.9%	32.4%	-0.3%	2.6%	-0.9%	5.7%
Bias median daily flow	3.5%	10.7%	22.0%	6.1%	37.2%	9.1%	-41.3%	4.1%	N/A	N/A
Bias median monthly flow	5.5%	4.5%	10.6%	-0.0%	19.5%	4.0%	-43.5%	6.6%	-0.8%	14.9%
Bias median annual flow	2.1%	4.0%	4.4%	1.0%	35.5%	35.8%	4.2%	1.5%	-1.1%	7.1%
Bias 10th percentile daily flow	9.6%	-7.0%	25.4%	-18.5%	4.4%	-7.8%	-25.7%	2.7%	N/A	N/A
Bias 10th percentile monthly flow	17.1%	7.6%	37.0%	-9.3%	-11.2%	-22.0%	-32.5%	4.8%	-7.6%	15.0%
Bias 90th percentile daily flow	1.4%	-1.0%	1.4%	-1.6%	60.2%	57.3%	23.3%	9.6%	N/A	N/A
Bias 90th percentile monthly flow	4.3%	-0.8%	-3.2%	0.5%	66.7%	51.4%	32.0%	-2.8%	-0.6%	-0.1%
Bias CV daily flow	-4.1%	-16.0%	-20.8%	-18.6%	-13.6%	-15.4%	6.2%	-2.6%	N/A	N/A
Bias CV monthly mean flow	2.3%	-4.0%	-13.8%	9.2%	5.7%	0.6%	26.5%	-10.5%	-4.9%	-10.7%
Bias CV annual mean flow	-12.7%	-3.5%	-12.3%	8.0%	7.8%	1.6%	25.0%	-11.0%	-0.9%	-7.9%
Bias January mean flow	6.0%	0.1%	8.4%	2.0%	58.6%	53.9%	-4.5%	9.5%	-0.6%	9.0%
Bias February mean flow	6.5%	-1.7%	-0.8%	4.2%	57.9%	66.4%	19.4%	2.3%	3.0%	1.5%
Bias March mean flow	4.3%	-5.2%	-11.6%	3.5%	50.7%	60.0%	26.2%	-5.5%	-2.9%	-8.4%
Bias April mean flow	5.3%	-4.6%	-12.4%	4.8%	51.6%	49.3%	31.0%	-7.6%	-0.3%	-7.4%
Bias May mean flow	11.6%	1.8%	-5.9%	11.1%	33.0%	10.3%	-1.4%	0.0%	-0.0%	-5.4%
Bias June mean flow	21.7%	18.7%	7.4%	12.6%	9.4%	-15.0%	-32.7%	0.1%	9.3%	10.7%
Bias July mean flow	12.3%	16.7%	15.1%	8.4%	-9.3%	-17.2%	-28.3%	0.9%	2.1%	17.3%
Bias August mean flow	12.9%	26.9%	27.0%	-3.4%	20.0%	-1.4%	-42.7%	4.1%	-4.7%	27.9%
Bias September mean flow	9.3%	26.0%	30.0%	2.7%	20.9%	-20.6%	-35.6%	7.2%	-4.6%	31.5%
Bias October mean flow	8.0%	10.1%	26.5%	2.7%	17.4%	7.1%	-7.8%	15.0%	-12.5%	22.1%
Bias November mean flow	1.7%	-4.6%	15.5%	-5.1%	24.2%	22.1%	-4.9%	6.1%	0.4%	19.9%
Bias December mean flow	-1.8%	-7.5%	11.6%	-9.0%	54.3%	56.9%	2.4%	8.9%	-5.6%	10.4%
NSE daily flow	0.62	0.73	0.69	0.42	0.19	0.13	-0.09	0.30	N/A	N/A
NSE monthly flow	0.83	0.83	0.84	0.59	0.30	0.30	0.65	0.79	0.84	0.74
NSE annual flow	0.76	0.80	0.81	0.49	-0.72	-0.47	-0.70	0.66	0.87	0.74

^a Note that these statistics are not directly comparable across models because they simulated different gauges over different time periods ranging from 4 to 48 years between 1951 and 2011.

^b Calibration levels include: (A) uncalibrated, (B) calibrated to downstream gauge, (C) calibrated specifically for site, and (D) calibrated specifically for site with adjusted precipitation, solar radiation, and potential evapotranspiration (PET) inputs.

CV = coefficient of variation; DAYMET = Daily Meteorological Data; HSPF = Hydrological Simulation Program-Fortran; IDW = Inverse Distance Weighted; MWBM = Monthly Water Balance Model; NR = Next-Generation Radar; NSE = Nash-Sutcliffe Efficiency; PRMS = Precipitation-Runoff Modeling System; SERAP = Southeast Regional Assessment Project; SWAT = Soil and Water Assessment Tool; WaSSI = Water Supply Stress Index model; WATER = Water Availability Tool for Environmental Resources; WaterFALL[®] = Watershed Flow and Allocation modeling system using NHDPlus.

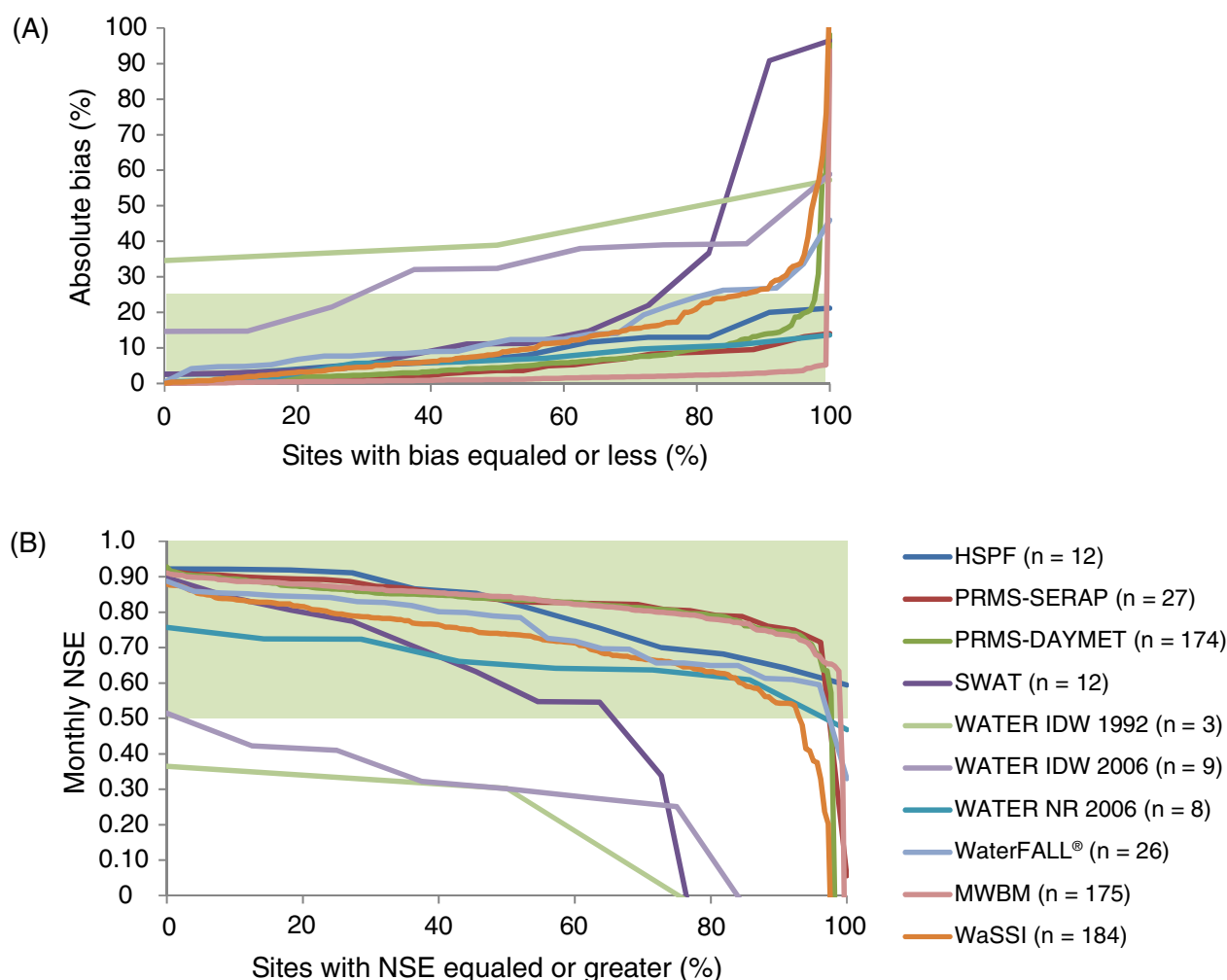


Figure 3.4—Distribution of bias in mean flow (A) and monthly NSE (B) across all sites simulated by each model. Only NSE values >0 are shown. The region highlighted in green is the bound for satisfactory model performance (Moriassi and others 2007) with monthly NSE >0.50 and bias in mean flow <±25 percent.

2007), all models had satisfactory or better performance at most sites (fig. 3.6). Model performance was satisfactory or better for mean streamflow bias (within ±25 percent of observed) with the exception of one site for SWAT (site 2, bias -26.2 percent, calibration level B), two sites for WaterFALL® (site 2, bias -33.7 percent, calibration level C; site 3, bias -48.0 percent, calibration level B), and one site for WaSSI (site 2, bias +25.0 percent, calibration level A). Similarly, model performance was satisfactory or better for monthly NSE (>0.50) with the exception of one site for SWAT (site 5, NSE 0.46, calibration level C) and one site for WaterFALL® (site 3, NSE 0.28, calibration level B). The median bias in mean streamflow across all models by site ranged from -12.0 percent at site 3 to +9.2 percent at site 4, while the median monthly NSE across models ranged from 0.72 at site 2 to 0.89 at site 1 (Caldwell and others 2015).

Differences in mean fit statistics across models by site were not significant ($p > 0.05$). The mean bias in mean flow across models by site ranged from -9.8 percent at site 1 to +7.2 percent at site 4, while the mean monthly NSE ranged from 0.47 at site 3 to 0.86 at site 4. The range in fit statistics among models for site 3 was greater than the other sites, with HSPF, SWAT, and WaterFALL® occurring as outliers compared to the other models and having considerably greater bias and lower NSE (table 3.8, fig. 3.5). The lower level of fit of these models for this site relative to the other models is likely because they were not calibrated for this site; rather, they were calibrated at a downstream gauge.

Increasing calibration intensity tended to improve model fit across sites and models (fig. 3.7). Calibration level A (uncalibrated) included only WaSSI simulations,

Table 3.7—Percent of gauges simulated by each model that could be considered satisfactory, good, and very good performance by monthly Nash-Sutcliffe Efficiency (NSE) and bias in mean flow criteria established by Moriasi and others (2007)

Model	Number of gauges	Monthly NSE			Bias mean flow		
		Satisfactory (>0.50)	Good (>0.65)	Very good (>0.75)	Satisfactory (within $\pm 25\%$)	Good (within $\pm 15\%$)	Very good (within $\pm 10\%$)
HSPF	12	100%	83%	67%	100%	83%	58%
PRMS-SERAP	27	96%	96%	89%	100%	100%	89%
PRMS-DAYMET	174	98%	96%	89%	98%	93%	80%
SWAT	12	67%	42%	33%	75%	67%	42%
WATER IDW 1992	3	0%	0%	0%	0%	0%	0%
WATER IDW 2006	9	11%	0%	0%	33%	22%	0%
WATER NR 2006	8	88%	50%	13%	100%	100%	75%
WaterFALL®	26	96%	77%	54%	81%	69%	46%
MWBM	175	99%	98%	86%	99%	99%	99%
WaSSI	184	93%	76%	45%	86%	70%	56%

DAYMET = Daily Meteorological Data; IDW = Inverse Distance Weighted; MWBM = Monthly Water Balance Model; NR = Next-Generation Radar; NSE = Nash-Sutcliffe Efficiency; PRMS = Precipitation-Runoff Modeling System; SERAP = Southeast Regional Assessment Project; SWAT = Soil and Water Assessment Tool; WaSSI = Water Supply Stress Index model; WATER = Water Availability Tool for Environmental Resources; WaterFALL® = Watershed Flow and Allocation modeling system using NHDPlus.

calibration level B (calibrated to downstream gauge) included three sites for HSPF and SWAT and two sites for WaterFALL®, calibration level C (calibrated specifically for site) included two sites for HSPF and SWAT and three sites for WaterFALL®, and calibration level D (calibrated for site with adjusted PPT, solar radiation, and PET inputs) included all PRMS-SERAP, PRMS-DAYMET, and MWBM simulations (table 3.5). The median absolute bias in streamflow across models and sites for a given level of calibration decreased from 15 and 17 percent for calibration levels A and B, respectively, to 6 percent for level C, to 3 percent for level D. Similarly, the monthly NSE tended to increase with increasing level of calibration. Median monthly NSE across sites and models for calibration levels A, B, C, and D, were 0.72, 0.68, 0.75, 0.85, respectively. Daily NSE across sites and daily time-step models also improved with increasing calibration (not shown), with median values of 0.39, 0.37, and 0.74 for calibration levels B, C, and D, respectively.

Evaluation of the water balance components at site 4 revealed the effect of modeling assumptions and calibration strategies on model fit statistics. Models generally over-predicted streamflow at site 4 (fig. 3.5), and thus calibration strategies for some models were aimed at either adjusting PPT (i.e., PRMS-SERAP, PRMS-DAYMET, and MWBM) or increasing losses through deep seepage (i.e., WaterFALL®) (table 3.5). Absolute streamflow over-prediction was most prevalent during the seasonally high-flow months of January, February, and March, but streamflow over-predictions expressed

as a percentage were highest in the low-flow months of July, August, and September (fig. 3.8B). Input for mean annual PPT was similar for HSPF, SWAT, WaterFALL®, and WaSSI, ranging from 1221 mm (WaterFALL®) to 1258 mm (HSPF and SWAT) for a total difference of approximately 3 percent (fig. 3.8A). Mean annual PPT for PRMS-SERAP, PRMS-DAYMET, and MWBM was reduced for site 4 during model calibration, resulting in decreases in mean annual PPT of approximately 9, 15, and 10 percent, respectively, whereas the other models did not adjust input PPT. WaterFALL® included deep seepage losses (approximately 127 mm, or 10 percent of PPT) to reduce streamflow predictions to more closely match observations by adjusting the seepage coefficients in the calibration process. Had deep seepage not been included, bias in mean streamflow for WaterFALL® may have increased from 11.3 to 44.2 percent, although other model parameters would have likely been adjusted to improve model fit. HSPF and SWAT simulations included consumptive use terms that also reduced streamflow predictions, amounting to approximately 33 mm and 67 mm, respectively. Had consumptive use not been considered, bias in mean streamflow would have increased from 9.3 to 18.0 percent for HSPF and from 5.1 to 22.5 percent for SWAT.

Differences in seasonal runoff bias among models can be partially explained by differences in ET estimates. Assuming no consumptive use or deep seepage losses, ET can be estimated as the difference between long-term mean annual PPT and runoff (fig. 3.8A). Using the

Table 3.8—Summary of classical model fit statistics for the seven select models compared in this study at the five common sites from 1980–1999

Site	Model	Calibration level ^a	Bias in mean streamflow (percent)	Monthly			Daily ^b		
				NSE	RMSE (cfs)	R ²	NSE	RMSE (cfs)	R ²
1	HSPF	C	-6.4	0.85	145.5	0.87	0.66	353.2	0.67
1	PRMS-SERAP	D	-1.8	0.92	115.8	0.92	0.80	265.5	0.81
1	PRMS-DAYMET	D	-2.5	0.92	103.9	0.93	0.87	208.2	0.88
1	SWAT	C	-3.6	0.56	255.5	0.79	0.36	544.5	0.56
1	WaterFALL®	C	4.6	0.90	119.0	0.91	0.59	429.1	0.67
1	MWBM	D	-1.4	0.89	135.3	0.89	—	—	—
1	WaSSI	A	-2.8	0.68	227.4	0.79	—	—	—
2	HSPF	B	2.6	0.71	147.2	0.73	-0.23	543.6	0.20
2	PRMS-SERAP	D	1.3	0.92	81.2	0.92	0.84	207.8	0.84
2	PRMS-DAYMET	D	0.1	0.86	102.5	0.87	0.60	292.6	0.60
2	SWAT	B	-26.2	0.64	137.7	0.75	0.41	253.3	0.44
2	WaterFALL®	C	-33.7	0.62	69.5	0.87	0.31	302.5	0.37
2	MWBM	D	-2.1	0.84	114.2	0.84	—	—	—
2	WaSSI	A	25.0	0.72	123.3	0.84	—	—	—
3	HSPF	B	-24.6	0.62	211.8	0.67	-0.18	855.1	0.26
3	PRMS-SERAP	D	-12.0	0.76	135.0	0.82	0.75	296.9	0.77
3	PRMS-DAYMET	D	-2.9	0.82	158.6	0.83	0.64	400.4	0.64
3	SWAT	B	-18.2	0.65	173.8	0.70	0.50	300.3	0.55
3	WaterFALL®	B	-48.0	0.28	114.2	0.61	0.38	378.1	0.43
3	MWBM	D	-6.6	0.85	157.7	0.86	—	—	—
3	WaSSI	A	-1.7	0.75	179.8	0.75	—	—	—
4	HSPF	B	9.2	0.92	506.5	0.93	0.74	1408.9	0.75
4	PRMS-SERAP	D	16.8	0.87	615.1	0.91	0.74	1569.1	0.75
4	PRMS-DAYMET	D	-0.3	0.89	577.6	0.89	0.67	1528.3	0.68
4	SWAT	B	5.0	0.86	725.6	0.88	0.63	1499.7	0.64
4	WaterFALL®	C	11.2	0.86	691.4	0.90	0.79	1383.5	0.80
4	MWBM	D	-8.4	0.83	755.5	0.85	—	—	—
4	WaSSI	A	16.2	0.77	858.6	0.82	—	—	—
5	HSPF	C	-2.1	0.75	283.2	0.77	0.37	667.3	0.46
5	PRMS-SERAP	D	3.9	0.83	235.1	0.85	0.80	370.6	0.80
5	PRMS-DAYMET	D	-15.3	0.73	280.9	0.82	0.47	525.1	0.50
5	SWAT	C	5.8	0.46	401.9	0.77	0.24	794.5	0.52
5	WaterFALL®	B	-15.1	0.83	182.0	0.88	0.17	761.8	0.37
5	MWBM	D	-9.4	0.77	265.3	0.79	—	—	—
5	WaSSI	A	15.4	0.69	300.9	0.81	—	—	—

^a Calibration levels include: (A) uncalibrated, (B) calibrated to downstream gauge, (C) calibrated specifically for site, and (D) calibrated specifically for site with adjusted precipitation, solar radiation, and potential evapotranspiration (PET) inputs.

^b The monthly MWBM and WaSSI models were not evaluated for prediction of ERFMs because many of the ERFMs require a daily time step to be calculated.

cfs = cubic feet per second; DAYMET = Daily Meteorological Data; IDW = Inverse Distance Weighted; MWBM = Monthly Water Balance Model; NR = Next-Generation Radar; NSE = Nash-Sutcliffe Efficiency; PRMS = Precipitation-Runoff Modeling System; R² = coefficient of determination; RMSE = root mean squared error; SERAP = Southeast Regional Assessment Project; SWAT = Soil and Water Assessment Tool; WaSSI = Water Supply Stress Index model; WATER = Water Availability Tool for Environmental Resources; WaterFALL® = Watershed Flow and Allocation modeling system using NHDPlus.

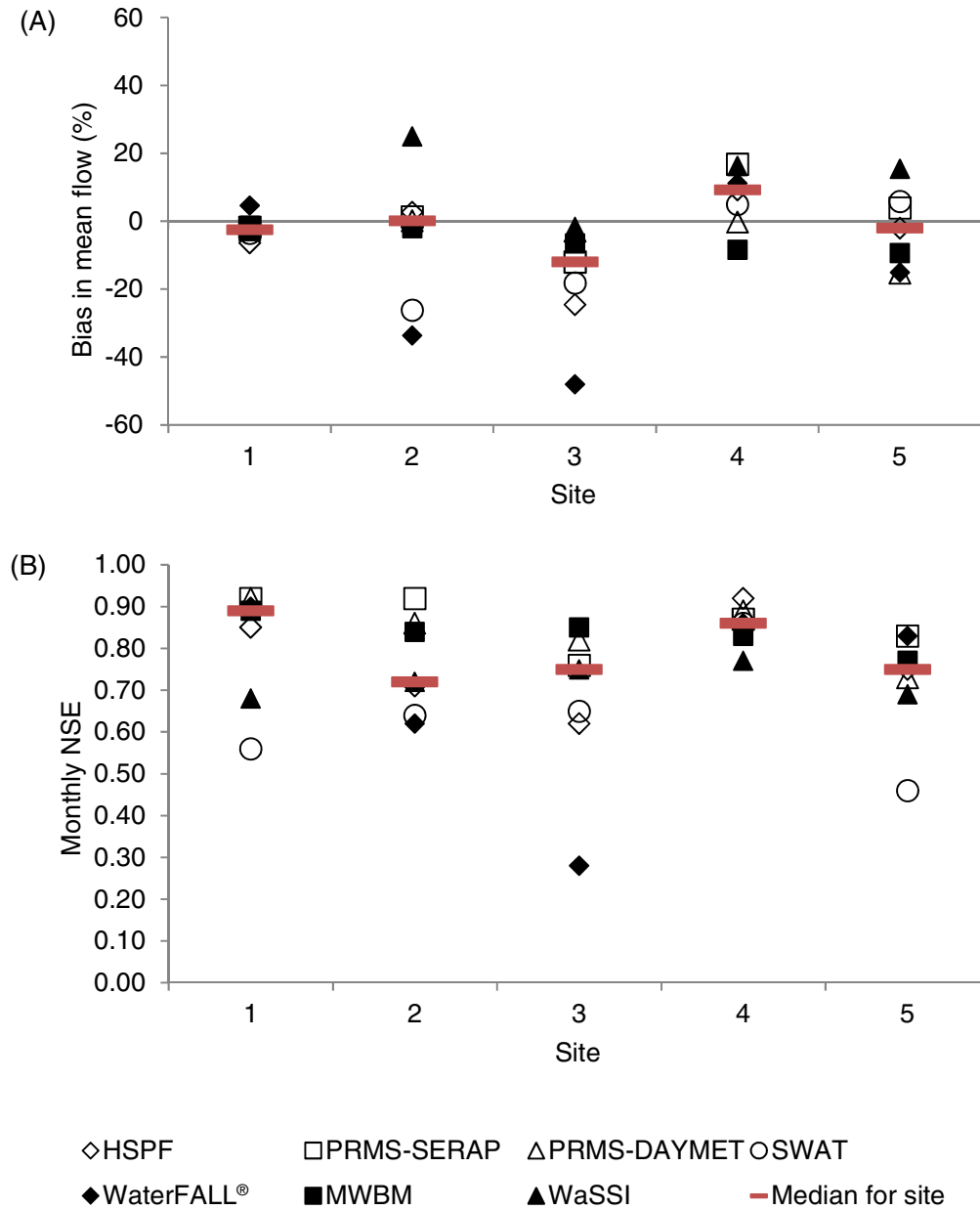


Figure 3.5—Distribution of selected classical model fit statistics across models by site for the flow time series from 1980–1999; bias in mean flow (A) and monthly NSE (B).

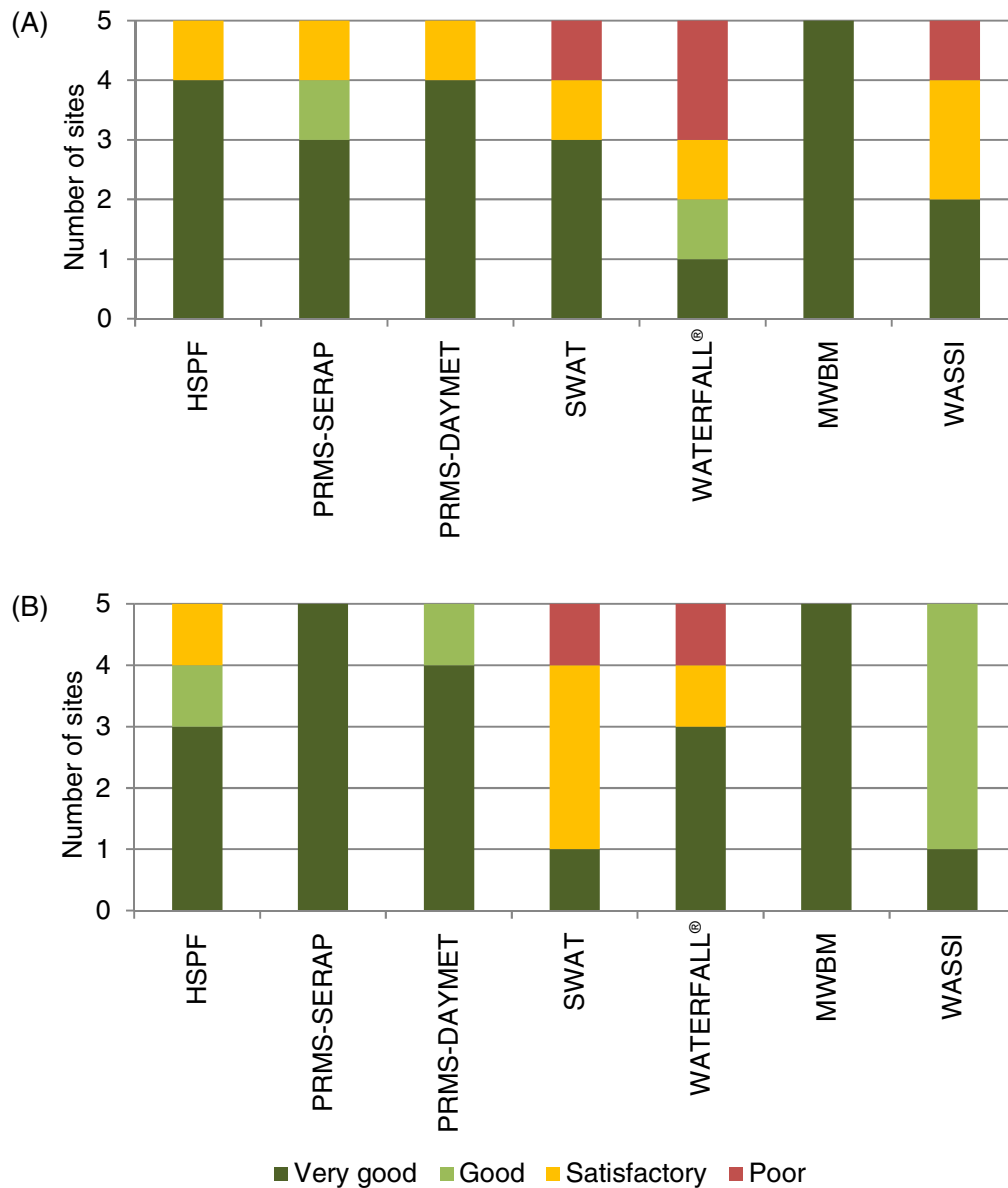
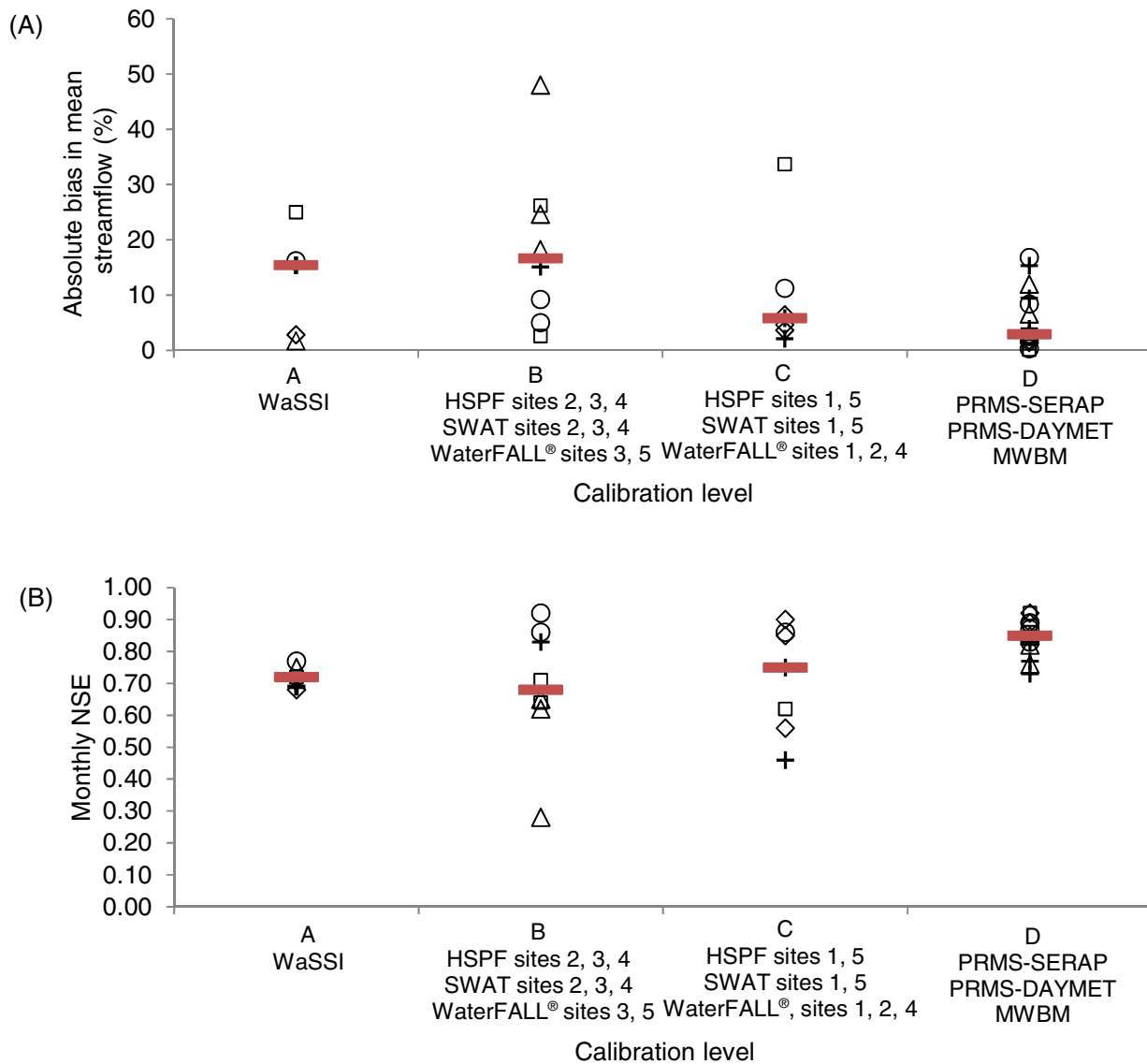


Figure 3.6—Distribution of sites falling into performance categories for absolute bias in mean flow (A) and monthly NSE (B) established by Moriasi and others (2007). Bias in mean flow within ± 25 , ± 15 , and ± 10 percent is considered to be indicative of satisfactory, good, and very good model performance, respectively, while monthly NSE values that are >0.50 , >0.65 , and >0.75 for prediction of monthly streamflow are indicative of satisfactory, good, and very good model performance, respectively.



◇ Site 1 □ Site 2 △ Site 3 ○ Site 4 + Site 5 — Median across sites at calibration level

Figure 3.7—Distribution of selected classical model fit statistics across sites by level of calibration for the 1980–1999 flow time series; absolute bias in mean streamflow (A) and monthly NSE (B). Calibration levels include A (uncalibrated), B (calibrated to downstream gauge), C (calibrated specifically for site), and D (calibrated specifically for site with adjusted precipitation, solar radiation, and PET inputs).

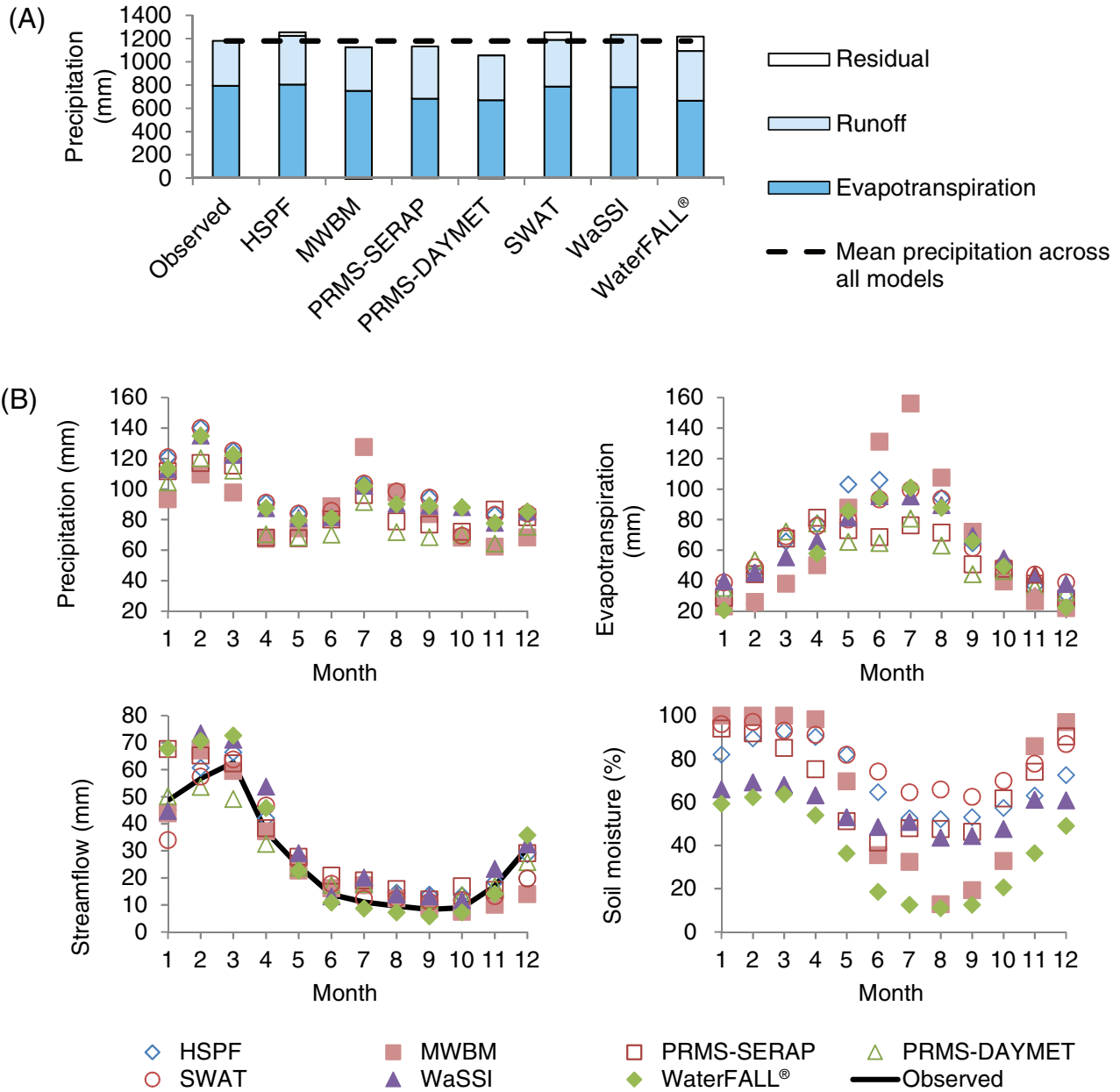


Figure 3.8—Partitioning of mean annual precipitation into evapotranspiration and runoff and residual lost to either consumptive use or deep seepage (A) and monthly median precipitation, evapotranspiration, soil moisture, and runoff (B) for all models at site 4: USGS gauge 02347500 Flint River at US 19 near Carsonville, GA. Runoff was computed by dividing discharge by drainage area. Observed ET was computed by taking the difference between the mean precipitation across models and the observed mean annual runoff at the gauge.

mean PPT across models as the mean PPT for the basin, estimated ET, calculated as the difference between mean PPT and runoff, was 797 mm. Bias in predicted ET was then 0.8, -14.4, -15.6, -1.4, -16.5, -5.9, and -1.7 percent for HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, WaterFALL®, MWBM, and WaSSI, respectively. There was good agreement between HSPF, SWAT, WaSSI, and the estimated observed mean annual ET. WaterFALL® predicted less ET relative to other models and the estimated observed ET, but the deep seepage term partially compensated for this difference. Soil moisture levels were considerably lower for WaterFALL® than the other models (fig. 3.8B), indicating that available soil water storage and/or recession coefficients may explain the lower ET estimates. The PRMS and MWBM models also under-predicted ET relative to other models and the estimated observed ET largely because PPT was reduced during model calibration.

The full suite of 175 flow metrics computed with the EflowStats package in R was evaluated for redundancy and reduced to a subset of 14 ERFMs which accounted for all five components of the flow regime (table 3.9). We evaluated differences between predicted and observed ERFMs across the five hourly and daily models; the monthly MWBM and WaSSI models were not evaluated for prediction of ERFMs because many of the ERFMs require a daily time step to be calculated (table 3.8). Overall bias in the prediction of the ERFMs among sub-monthly time-step models varied by site and by flow metric (fig. 3.9), with no model or calibration level clearly having superior predictive performance for all sites and metrics (table 3.10). The median absolute bias across all ERFMs and sites was 19.4, 19.1, 18.7, 31.9, and 24.1 percent for HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, and WaterFALL®, respectively. Increasing calibration tended to reduce bias for individual models

Table 3.9—Definitions of the reduced set of 14 ecologically relevant flow metrics (ERFMs) used in this study to describe the five primary components of the flow regime

Streamflow component	ERFM	Description	Unit of measurement
Magnitude (M)	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)
	MA25	Variability of February flow values: Compute the standard deviation for each month in each year. Divide the standard deviation by the mean for each month and take the mean of these values for each month across years.	percent
	ML6	Minimum June streamflow: minimum June streamflow across the period of record	cfs
	ML9	Minimum September streamflow: minimum September streamflow across the period of record	cfs
	ML21	Variability of annual minimum flows: Compute the standard deviation of annual minimum streamflow and divide by the mean annual minimum streamflow.	percent
	MH20	Specific mean annual maximum flow: Divide mean annual maximum flow across the period of record by watershed area.	cfsm
Frequency (F)	FL1	Frequency of low flood: low flood pulse count	n/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 (D)	DL17	Variability in low pulse duration: standard deviation for the yearly average low-flow pulse durations (daily flow less than the 25th percentile)	percent
	DH20	High flow duration	days
	DL4	Mean of the annual minimum 30-day average flows	cfs
	DH4	Mean of the annual maximum 30-day moving average flow for the entire record	cfs
Timing (T)	TH1	Average Julian date of the annual maximum flow for the entire record	Julian day
Rate of change (RA)	RA4	Variability of the fall rate for the entire record	percent

A = average; L = low or minimum flow; H = high or maximum flow.

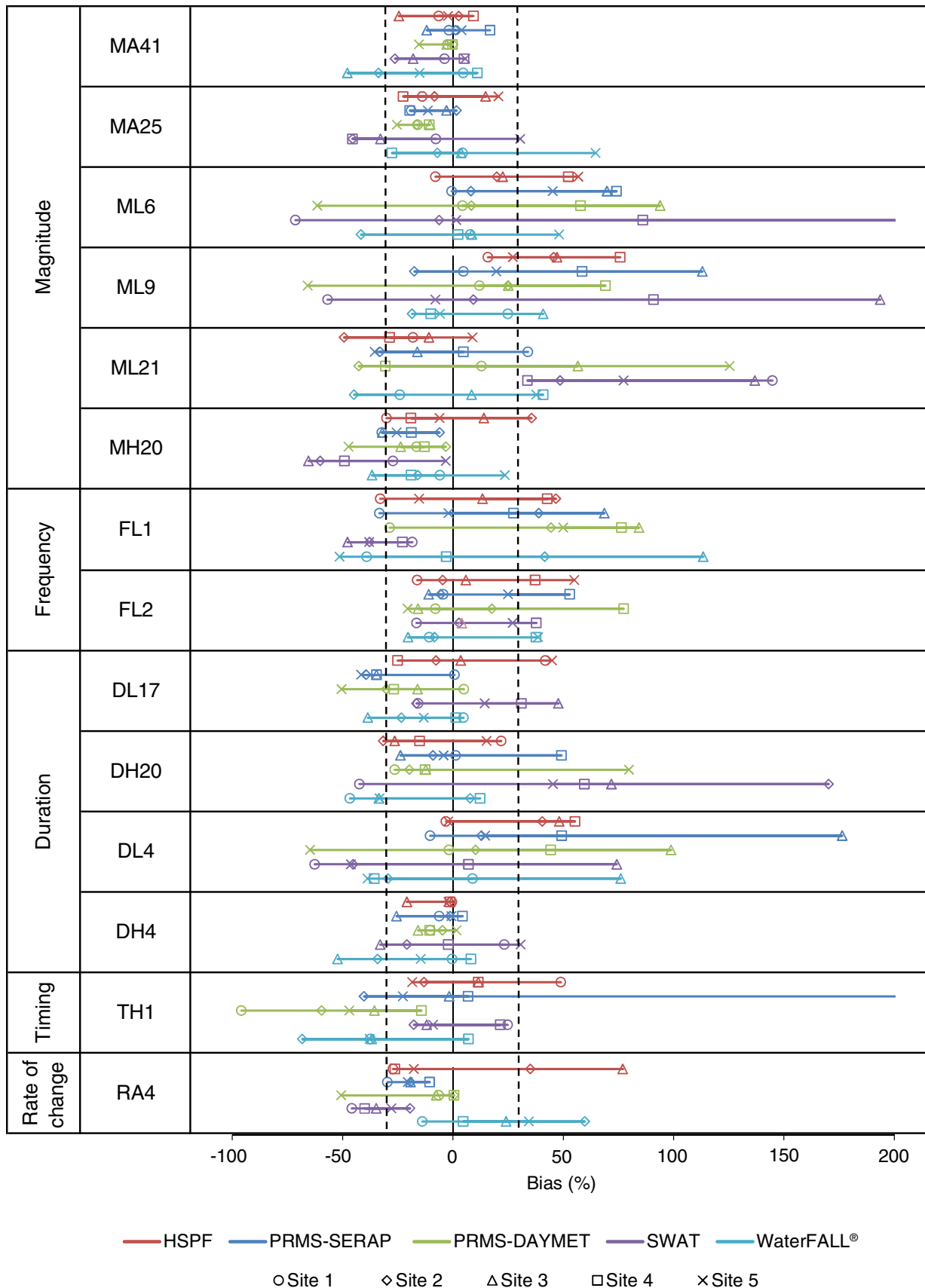


Figure 3.9—Bias in prediction of the 14 ERFMs across the five study sites for the daily time-step hydrologic models. [See table 3.9 for definitions of ERFMs.]

Table 3.10—Observed and predicted ecologically relevant flow metrics^a for the five sites used in this study

	Site	Magnitude						Frequency		Duration				Timing	Rate of change
		MA41 (cfs/m)	MA25 (%)	ML6 (cfs)	ML9 (cfs)	ML21 (%)	MH20 (cfs/m)	FL1 (n/ year)	FL2	DL17 (%)	DH20 (days)	DL4 (cfs)	DH4 (cfs)	TH1 (Julian day)	RA4
Observed	1	2.40	62.0	446.5	276.8	37.8	21.99	13.7	67.0	42.9	7.9	303.2	1,530.5	21	342.5
HSPF	1	2.25	53.4	411.1	320.6	31.0	15.37	9.2	56.1	60.8	9.6	293.6	1,523.7	31	249.4
PRMS-SERAP	1	2.36	50.3	444.1	289.9	50.7	14.90	9.2	64.0	43.2	8.0	271.8	1,434.5	362	240.9
PRMS-DAYMET	1	2.34	52.1	465.9	309.9	42.7	18.36	9.8	61.6	45.1	5.8	297.8	1,373.5	1	320.4
SWAT	1	2.31	57.3	127.7	119.6	92.5	16.03	11.2	55.9	36.1	4.5	113.1	1,886.1	26	185.5
WaterFALL®	1	2.51	64.7	481.8	345.7	28.7	20.68	8.4	59.8	44.9	4.2	330.1	1,524.2	13	294.9
Observed	2	1.49	90.1	92.2	51.2	62.4	17.62	9.5	40.8	45.8	5.4	59.9	1,007.3	58	269.3
HSPF	2	1.53	82.6	110.5	74.6	31.6	23.90	13.9	38.9	42.3	3.7	84.1	993.2	50	363.8
PRMS-SERAP	2	1.51	91.5	99.6	42.2	41.8	16.56	13.2	38.5	27.8	4.9	67.6	994.1	35	217.6
PRMS-DAYMET	2	1.49	75.2	99.9	64.0	35.7	17.06	13.7	48.0	32.0	4.3	66.1	959.6	23	270.6
SWAT	2	1.10	49.1	86.4	56.0	92.7	7.03	5.9	41.9	38.3	14.5	32.8	797.4	48	217.0
WaterFALL®	2	0.99	83.8	53.8	41.7	34.5	14.82	13.4	37.4	35.1	5.8	42.3	663.9	18	430.3
Observed	3	1.26	92.1	42.6	26.5	41.3	27.95	7.1	46.9	41.5	8.4	25.5	1,495.6	60	418.3
HSPF	3	0.95	105.7	52.2	39.0	36.8	31.86	8.0	49.7	43.0	6.2	37.8	1,183.2	67	740.3
PRMS-SERAP	3	1.11	89.4	72.4	56.5	34.7	18.99	11.9	41.7	27.1	6.4	70.4	1,112.5	59	338.0
PRMS-DAYMET	3	1.23	82.5	82.6	33.2	64.7	21.34	13.0	39.5	34.9	7.3	50.7	1,259.5	38	386.9
SWAT	3	1.04	61.8	156.3	77.8	97.9	9.65	3.7	48.8	61.4	14.4	44.4	1,002.9	53	273.1
WaterFALL®	3	0.66	95.5	46.3	37.3	44.8	17.71	15.1	37.3	25.5	5.6	44.9	713.3	38	519.1
Observed	4	1.12	73.0	475.3	302.5	42.9	14.79	6.9	30.5	44.4	9.4	342.8	6,650.1	52	296.9
HSPF	4	1.22	56.5	723.8	531.7	30.6	11.98	9.8	41.9	33.2	8.0	532.5	6,562.3	58	218.9
PRMS-SERAP	4	1.31	58.7	827.6	479.6	45.0	12.02	8.8	46.7	29.0	14.1	511.5	6,941.4	55	265.6
PRMS-DAYMET	4	1.12	65.1	750.2	511.5	29.8	12.88	12.2	54.2	32.5	8.3	494.9	5,948.9	44	298.4
SWAT	4	1.17	39.7	884.3	577.5	57.4	7.52	5.3	42.1	58.1	15.1	366.9	6,511.7	63	177.9
WaterFALL®	4	1.24	52.8	486.2	272.2	60.5	11.99	6.7	42.0	45.0	10.6	220.7	7,191.2	55	310.7
Observed	5	1.19	48.1	197.8	196.3	37.3	11.36	7.9	38.2	58.4	11.4	202.9	2,014.0	47	338.0
HSPF	5	1.17	58.1	310.2	249.7	40.6	10.67	6.7	59.2	84.7	13.1	198.7	1,973.4	38	278.1
PRMS-SERAP	5	1.24	42.7	287.2	234.9	24.1	8.46	7.7	47.8	34.1	10.9	232.5	1,999.4	36	268.8
PRMS-DAYMET	5	1.01	35.9	76.2	67.3	84.1	5.99	11.8	30.4	28.9	20.5	71.5	2,046.9	25	166.7
SWAT	5	1.26	62.8	200.8	180.8	66.2	11.00	4.9	48.6	66.9	16.5	109.1	2,632.4	43	243.8
WaterFALL®	5	1.01	79.3	293.2	184.8	51.4	14.04	3.8	53.0	50.7	7.6	124.4	1,719.4	29	454.4

^a See table 3.9 for definitions of ecologically relevant flow metrics.

cfs = cubic feet per second; cfs/m = cubic feet per second per square mile; DAYMET = Daily Meteorological Data; HSPF = Hydrological Simulation Program-Fortran; SERAP = Southeast Regional Assessment Project; PRMS = Precipitation-Runoff Modeling System; SERAP = Southeast Regional Assessment Project; SWAT = Soil and Water Assessment Tool; WaterFALL® = Watershed Flow and Allocation modeling system using NHDPlus.

overall, with median absolute bias across all sites and ERFMs decreasing from calibration level B to level C for HSPF (22.6 percent for level B, 16.9 percent for level C), SWAT (36.2 percent for level B, 27.1 percent for level C), and WaterFALL® (36.7 percent for level B, 14.9 percent for level C). The median absolute bias across all sites and ERFMs for calibration level D (19.1 percent) was similar to that of all models at calibration level C (18.4 percent).

All models had at least one flow metric falling outside the ± 30 -percent range of hydrologic uncertainty at every site (figs. 3.9 and 3.10A). The number of ERFMs out of the total of 14 (table 3.9) that fell outside this range at three or more of the five sites included three, four, five, nine, and five for HSPF, PRMS-SERAP, PRMS-DAYMET, SWAT, and WaterFALL®, respectively. Some of the magnitude, frequency, and duration ERFMs tended to be better represented across models than others. For example, MA41 (mean annual runoff), FL2 (variability in low-pulse count), and DH4 (mean of annual maximum 30-day average flow) were generally well predicted, with bias outside the range of uncertainty at less than three of the five sites for all models. Bias in FL1 (frequency of low flood), however, was outside the range of uncertainty for three or more of the five sites for all models, and bias in ML21 (variability of annual minimum flows) and DL4 (mean of annual minimum 30-day average flows) was outside the range of uncertainty for three or more of the five sites for four of the five models. The hydrologic models evaluated in this study generally had lower bias in the prediction of flow metrics representing mean flows (e.g., MA41) than metrics representing the extremes of flow (e.g., FL1), particularly low-flow conditions. Bias was greater for many of the low-flow metrics due to the low absolute magnitudes of these metrics (table 3.10, fig. 3.9). This result is a fairly common outcome for many modeling studies due to choices made during the calibration process; however, it should be noted that this modeling bias may directly affect the predictive capacity of flow-ecology response models derived using ERFMs that fall outside the established range of uncertainty.

There was considerable variability in ERFM predictive performance across sites (table 3.10, figs. 3.9 and 3.10B). The ERFMs (table 3.9) with prediction bias outside the range of hydrologic uncertainty for three or more of the five models included FL1 and TH1 for site 1 (two of 14 ERFMs); ML21, FL1, and TH1 for site 2 (three of 14); ML6, ML9, MH20, FL1, DL17, and DL4 for site 3 (six of 14); ML6, ML9, ML21, FL2, and DL4 for site 4 (five of 14); and ML6, ML21, FL1, DL17, DH20, and DL4 for site 5 (six of 14). The ERFMs at site 1 were generally well predicted, likely reflecting the fact that (1) all models were calibrated for this site (i.e., calibration levels C and D),

(A)

MA41					
MA25					
ML6					
ML9					
ML21					
MH20					
FL1					
FL2					
DL17					
DH20					
DL4					
DH4					
TH1					
RA4					
	HSPF	PRMS-SERAP	PRMS-DAYMET	SWAT	WATERFALL®

(B)

MA41						
MA25						
ML6						
ML9						
ML21						
MH20						
FL1						
FL2						
DL17						
DH20						
DL4						
DH4						
TH1						
RA4						
	Site 1	Site 2	Site 3	Site 4	Site 5	

	0
	1
	2
	3
	4
	5

Figure 3.10—Number of sites per model out of a total of five (A) and number of models per site out of a total of five (B) for which bias in the 14 ERFMs fell outside of the ± 30 -percent range of hydrologic uncertainty. Monthly models (MWBm and WaSSI) are not shown because computation of most ERFMs used in this study requires a daily time step. [See table 3.2 for hydrologic model definitions and table 3.9 for definitions of ERFMs.]

and (2) the watershed upstream of the site was mostly low-intensity forested land (table 3.4) and likely had fewer flow alterations that may affect model performance. Although sites 1 and 3 had similar levels of urban development, ERFMs were not as well predicted at site 3. In particular, those ERFMs relating to low flows (e.g., ML6, ML9, FL1, DL17, and DL4) were generally over-predicted with bias exceeding 30 percent (fig. 3.10B). The HSPF, SWAT, and WaterFALL® models were not specifically calibrated for site 3 (calibration level B), which may explain the higher bias for this site, but the PRMS-SERAP and PRMS-DAYMET models, calibrated specifically for this site, (calibration level D) also had higher bias for ERFMs at site 3 than site 1, indicating that there may be underlying natural (e.g., higher than expected ET losses) and/or anthropogenic processes (e.g., surface and groundwater use, interbasin transfers, water diversions, etc.) that are not being accounted for in the models despite the fact that these sites are assumed to be minimally altered. Most model predictions of ERFMs for site 2 were within the range of uncertainty despite having higher levels of urban development (table 3.4), except that ML21 (variability in annual minimum flows) was generally under-predicted, FL1 (frequency of low flood) was generally over-predicted, and TH1 (average Julian date of annual maximum flow) was generally under-predicted (table 3.10, fig. 3.9). The ERFMs relating to low flows were generally over-predicted by most models for site 4 (e.g., ML6, ML9, FL2, and DL4) and site 5 (e.g., ML6 and ML21).

DISCUSSION

The intent of this model comparison study was not to suggest that the performance of any particular model is superior to that of the others. Rather, we were interested in understanding differences among hydrologic models and calibration strategies by quantifying and comparing the potential causes of error associated with model prediction and testing our hypotheses that (1) in general, regional-scale hydrologic models (e.g., MWBM, WaSSI) would have poorer predictive capacity and higher levels of uncertainty than the fine-scale models (e.g., HSPF, PRMS, SWAT, WaterFALL®); and (2) models with higher levels of calibration would perform better than those that were less calibrated. In order to accomplish these objectives, we summarized a subset of classical model fit statistics (e.g., mean bias, R^2 , RMSE, and NSE) for seven hydrologic models of varying calibration intensity across five study sites where modeling efforts overlapped with USGS continuous record gauges.

We found that all models had “satisfactory” or better performance (as defined in this paper) at most sites. Comparing classical model fit statistics across all sites, the broad-scale MWBM and WaSSI had comparable

error in predicting observed streamflows at the monthly time step as that of the fine-scale HSPF, PRMS, SWAT, and WaterFALL® models (fig. 3.5), which refutes our hypothesis that regional-scale models have poorer predictive performance than fine-scaled models at the monthly time step. For example, according to monthly NSE criteria (Moriassi and others 2007), the uncalibrated WaSSI model predictions would be considered “good” at all of the five sites simulated by multiple models and “very good” at one site, while the calibrated MWBM predictions would be “very good” at all sites (fig. 3.6B). Achieving good model fit at the monthly time step with either monthly or smaller time-step models generally indicates that the correct balance of PPT and ET is represented, but it does not necessarily indicate that the separation between surface and subsurface flows is accurately represented. Thus, good model fit in monthly time-step simulations may not indicate that the model would be useful in answering resource questions that require detailed information regarding surface runoff and baseflows.

We also found evidence supporting our hypothesis that increasing calibration intensity generally improved model fit across sites and models. For classical model fit statistics, the more intensive site-specific calibrations (levels C and D) generally decreased bias and increased NSE at the monthly scale relative to uncalibrated models (level A) and models calibrated to a downstream site (level B); however, differences between calibration levels A and B were not as large (fig. 3.7). For ERFMs, increasing calibration tended to reduce bias for individual models overall, but no model or calibration level clearly had superior predictive performance for all sites and ERFMs. For example, bias in ERFM predictions was generally lower for sites calibrated at level C than for sites calibrated at level B for HSPF, SWAT, and WaterFALL®. However, differences in ERFM bias between models calibrated for sites at level C and models calibrated for sites at level D were generally smaller. Clearly, adjusting PPT, solar radiation, and PET during model calibration (i.e., calibration level D) can result in improved model fit relative to other levels of calibration; however, caution should be used when applying models calibrated in this manner to make projections using other sources of climate input (e.g., future climate change scenarios). For example, it is common to use a climate dataset based on historical weather observations to calibrate a model and to use one or more downscaled climate datasets produced by General Circulation Models (GCMs) for future scenarios. Often the GCM-predicted climate variables will differ from observations in magnitude and distribution over the historical period. If historical observed climate data are adjusted in the calibration process to achieve a better model fit to streamflow observations, then a modeler would need to determine how to incorporate

this adjustment into the model when the GCM-predicted climate variable over the historical period may be different than the observed variable used to derive the adjustment factors. While this could be done, the modeler would need to exercise caution in doing so. In addition to model calibration, model inputs and assumptions also played a role in predictive performance. For example, the WaterFALL® model used land cover from the 1970s (with lower levels of impervious cover than in 2001 or 2006 used by other models) and tended to have negative bias for sites with some level of urbanization (e.g., site 2) because surface runoff was lower.

Similar to other ecological flow modeling studies (Murphy and others 2013, Wenger and others 2010), the sub-monthly time-step models evaluated in this study tended to have “good” predictive performance for ERFMs representing the mean of flow, but had difficulty in predicting flow metrics related to low or extreme flows (table 3.10, figs. 3.9 and 3.10). The variability in prediction bias across ERFMs for the sub-monthly models is indicative of the variability in level of calibration across models and sites but also the challenges associated with calibrating hydrologic models for all streamflow conditions. Model calibration is generally intended to capture the variability and mean magnitude of streamflow. It is nearly impossible to calibrate models to fit the entire range of observed streamflows because adjusting model parameters to fit a portion of the flow regime has an effect on how well the model fits observed streamflows outside of that range. For example, WaterFALL® was calibrated to log-transformed daily streamflows (table 3.5) to provide improved fit for low flows, but calibrating in this way can degrade fit for high or median flows. There was considerable variability in classical fit statistics and ERFM predictive performance across sites (figs. 3.5, 3.9, and 3.10). Fit statistics and ERFMs at some sites (e.g., site 1) were better predicted by all models than other sites (e.g., site 3), illustrating the fact that model performance is site-specific regardless of model framework or level of calibration. These findings may have implications for the development of flow-ecology response models because it is often the low flows (baseflows), annual-flow pulses, and seasonality of high flows that provide the conditions necessary to support natural-assemblage complexity (Matthews 2005, Poff and Ward 1989, Poff and others 1997, Richter and others 1997, Stanford and others 1996). Because streamflow models in this study tended to perform better when predicting mean ERFMs than when predicting low or extreme flow ERFMs, great care should be taken when using ERFMs with high prediction bias (e.g., ML6, ML9, FL1, DL17, and DL4) to develop flow-ecology response models.

Other approaches to predicting ERFMs (e.g., regression models) have been recently shown to have better predictive performance for low-flow metrics (Knight and others 2012, Murphy and others 2013). However, rainfall-runoff and other physically based hydrologic models are still needed for evaluating environmental change and hydrologic alteration effects on aquatic ecosystems because they are more flexible and can simulate scenarios of change. Additionally, even though some regression models appear to perform well in parts of the SEUS, it is difficult to predict whether they will show the same level of performance or have a high level of transferability in the snowmelt-driven Rocky Mountain States or in areas such as the Southwestern United States where low flows predominate and where there are fewer gauges available to establish statistical relations. While rainfall-runoff models are more flexible and can simulate scenarios of change, it should be kept in mind that all hydrologic models, regardless of their level of complexity, are simplified mathematical representations of natural systems and therefore may not adequately reflect all of the processes that affect streamflow and/or may not adequately predict streamflow response to environmental change. Further, uncertainty of hydrologic model predictions are inherently dependent on the uncertainty of model inputs (e.g., soils, land cover, climate).

LIMITATIONS

While this report likely represents what may be the most rigorous evaluation of the use of hydrologic models for flow-ecology science compiled for the SEUS, we acknowledge that it may provide a limited overview of the many tools and techniques available. Some limitations of this study include:

1. Only a subset of the available hydrologic models were considered in this study.
2. The models evaluated were not developed using the same calibration objective functions and input datasets, making it difficult to separate differences in model performance that may be related to the model framework (e.g., HSPF or PRMS) from differences associated with the choice of model inputs and calibration.
3. New methods are being developed all the time. The findings in this report are not stationary and should be reevaluated from time to time.
4. The capacity to fully understand non-stationary conditions associated with climate change requires rigorous calibration of models and careful attention to model inputs and representation of physical processes that may assume stationarity. For example, adjusting PPT and other climate variables may improve model fit

for historical flow observations, but these adjustments may not be appropriate when using the model to make projections using other sources of climate input (e.g., future climate change scenarios).

5. Models evaluated were applied to several basins in SEUS region. The relative model performance may be different in other hydroclimatic settings (e.g., snowmelt-dominated streams and streams in arid climates).
6. There are tradeoffs between regional- and fine-scale models. Regional-scale models are often easier to parameterize but are often of a coarser resolution in space and time. Fine-scale models are often more difficult to parameterize but can have finer resolution and smaller time steps. Resource managers should consider the desired resolution of streamflow predictions when selecting a model for addressing a particular resource problem and balance the need for that resolution with the expense in input data requirements, computational limitations, and desired level of uncertainty.
7. In this study, we have demonstrated that similar levels of model performance may be obtained at the monthly time step using regional- and fine-scale hydrologic models. We have also shown that regional-scale and some fine-scale hydrologic models predict similar changes in runoff for a given change in climate inputs. However, these results only provide a demonstration of the potential of multi-scale modeling approaches to evaluate environmental change effects on streamflow and ecological response. Due to differences in land cover input data, we were not able to determine whether there would be similar streamflow response to land cover change among the models evaluated. Additional study is required to determine the best way to use regional- and fine-scale models to identify hot spots and develop flow-ecology relations, respectively. Models should be developed using the same inputs and calibration objective functions and then used to evaluate the same scenarios of climate and land cover change.
8. There are tradeoffs between calibrating models to best match observed high-flow or low-flow portions of the hydrograph that may affect flow-ecology modeling. Model calibration is generally intended to capture the variability and the central tendency of streamflow. It is nearly impossible to calibrate models to fit the entire range of observed streamflows because adjusting model parameters to fit a portion of the flow regime has an effect on how well the model fits observed streamflows outside of that range. For example, it is fairly common for many modeling studies to have relatively large

biases in the prediction of low-flow ERFMs due to choices made during the calibration process; however, it should be noted that this modeling bias may directly affect the predictive capacity of flow-ecology response models derived using ERFMs that fall outside the established range of uncertainty.

Despite these limitations, it is our hope that this rigorous approach to understanding differences in streamflow predictions among a subset of hydrologic models currently in use in the SEUS and developing flow-ecology response models will provide water resource managers and stakeholders with an informed pathway for developing the capacity to link streamflow and ecological response and an understanding of some of the limitations associated with these type of modeling efforts.

CONCLUSIONS

The primary objective of this study was to provide resource managers and environmental flow practitioners with some insight into the relative error in streamflow predictions among a subset of hydrologic models commonly used for water supply assessment, environmental flow studies, and climate change predictions. All of the models evaluated were developed by different agencies, for different purposes, with different input datasets, and, in general, were calibrated to different degrees using different objective functions. As a result, we could not separate the relative effect of model structure on prediction error from that of model calibration and modeler expertise. To fully evaluate the effect of model structure alone, all models should be developed using the same inputs and calibrated to meet the same objective functions. However, our results do not indicate that any specific hydrologic model is superior to the others evaluated at all sites and for all measures of model performance, and do not support the hypothesis that regional-scale models have less predictive power than fine-scale models at a monthly time step. Differences among model predictions for specific fit statistics or ERFMs are as likely to be related to differences in model calibration strategy as they are related to differences in model structure. As a result, we do not provide recommendations of one hydrologic model over another based on the results of this study. Instead we stress that it is incumbent upon resource managers, environmental flow practitioners, and policymakers to consider the expertise of the modeler, the applicability of a model to a particular resource problem, the context to which the model is being applied, the scale of interest, and the important components of the flow regime that may be used for model calibration to minimize error across the targeted range of flows and thus improve flow-ecology relations.

CHAPTER 4

Feasibility of Combining Regional- and Local-Scale Models to Identify Unique Areas of Concern and Understand Fine-Scale Hydrologic Dynamics Under Climate Change

INTRODUCTION

Leveraging the benefits of both large-scale models and high-resolution models has the potential to allow more robust environmental change assessment studies to balance water resources needed to support aquatic assemblages while conserving water for long-term human needs across broad regions. For example, the Water Supply Stress Index (WaSSI) model, a regional-scale monthly water balance and flow routing model (Caldwell and others 2012, Sun and others 2011b) is used to evaluate the effects of environmental change on water supply and river flows. The model is run uncalibrated using off-the-shelf databases and thus could be used to more broadly assess environmental change effects and identify specific areas of concern (“hot spots”) where the combined effects of land cover change, climate change, and/or flow alteration may threaten water resources. Fine-scale, physically based models of higher temporal resolution, such as the Hydrological Simulation Program-Fortran (HSPF) and the Soil and Water Assessment Tool (SWAT), could then be applied to those areas of concern to provide higher resolution quantitative estimates of changes in water supply and ecologically relevant flow metrics (ERFMs) using more site-specific inputs. To apply such a multi-scale modeling approach, the variability of predicted streamflow response to different stressors across large- and fine-scale models must be assessed. For example, for a given change in precipitation (PPT), do the models predict similar changes in streamflow? The aim of this study was to examine the potential for combined application of large- and fine-scale hydrologic modeling approaches over large regions for climate change assessment studies. This was done by quantifying differences in sensitivity to climate change (i.e., PPT and temperature [TEMP]) among hydrologic models.

METHODS

Study Site

The study site chosen for this assessment was U.S. Geological Survey (USGS) gauge 02347500 (Flint River at US 19, near Carsonville, GA) located in the Apalachicola-Chattahoochee-Flint (ACF) Basin (fig. 4.1). The upstream drainage area of this site is 4792 km², with mean annual PPT and TEMP of 1282 mm and 16.8 °C, respectively.

Predominant land cover consists of 13.9 percent developed land (3.6 percent impervious), 55 percent forest, and 16 percent agriculture, with woody wetland (5.6 percent), grassland (5.3 percent), shrubland (2.6 percent), open water (1.4 percent), and barren (0.2 percent) land covers comprising the remaining area of the basin (Falcone and others 2010, 2011). The headwaters of this basin drain portions of the city of Atlanta, GA. The ACF Basin has been subject to water shortages and development pressure in the past and thus has been intensely studied over the last decade with multiple modeling efforts taking place to evaluate drought and environmental change effects on water supply and aquatic ecosystems (e.g., Freeman and others 2013, Georgakakos and others 2010, LaFontaine and others 2013).

Model Descriptions

Models included in this study were among those discussed and compared in the model comparison workshop (see chap. 3): Hydrological Simulation Program-Fortran (HSPF), the Soil and Water Assessment Tool (SWAT), the Generalized Watershed Loading Function (GWLf)-based WaterFALL[®] model developed by Research Triangle Institute (RTI), and the U.S. Department of Agriculture (USDA) Forest Service Water Supply Stress Index (WaSSI) model (table 4.1). The two parameterizations of Precipitation-Runoff Modeling System (PRMS) and the Monthly Water Balance Model (MWBm) (see chap. 3) were not included in this analysis because PPT and TEMP inputs for these models were adjusted in the calibration process and thus were not comparable to the climate inputs of HSPF, SWAT, WaterFALL[®], and WaSSI. The WaSSI model is a regional, large-scale model, while HSPF, SWAT, and WaterFALL[®] are more complex, highly parameterized fine-scale models. All of the models evaluated in this study were developed by different agencies, for different purposes, and calibrated to different degrees using different objective functions as described below (Caldwell and others 2015).

HSPF and SWAT

Both the HSPF and SWAT models used in this study were implemented by Tetra Tech as part of a larger study to characterize the sensitivity of streamflow, nutrient loading, and sediment loading to a range of potential



Figure 4.1—Map of the Apalachicola-Chattahoochee-Flint Basin highlighting the location of the Flint River at US 19 near Carsonville, GA (USGS gauge 02347500).

Table 4.1—General summary of hydrologic model attributes

Model	HSPF	SWAT	WaterFALL®	WaSSI
Spatial resolution	HUC-10 (~410 km ²)	HUC-10 (~410 km ²)	NHDPlus catchment (~1.0 km ²)	HUC-12 (~80 km ²)
Land cover input	2001 NLCD (Homer and others 2007)	2001 NLCD (Homer and others 2007)	ca. 1970s USGS GIRAS (Price and others 2006)	2006 NLCD (Fry and others 2011)

GIRAS = Geographic Information Retrieval and Analysis System; HSPF = Hydrological Simulation Program-Fortran; HUC = Hydrologic Unit Code; NHD = National Hydrography Dataset; NLCD = National Land Cover Database; PRISM = Parameter-elevation Relationships on Independent Slopes Model; SWAT = Soil and Water Assessment Tool; USDA = U.S. Department of Agriculture; USGS = U.S. Geological Survey; WaSSI = Water Supply Stress Index model; WaterFALL® = Watershed Flow and Allocation modeling system using NHDPlus.

mid-21st century climate futures in 20 large U.S. drainage basins (Johnson and others 2012, USEPA 2013). Model descriptions and information pertinent to this application are detailed below.

HSPF—The HSPF (Bicknell and others 2001, 2005) is a hydrology and water quality model commonly used for determination of Total Maximum Daily Loads to receiving waters in response to the Clean Water Act. HSPF is a well-documented watershed model that computes the water balance based on the Stanford Watershed Model (Crawford and Linsley 1966) in multiple surface and subsurface layers at an hourly time step. The water balance is simulated based on Philip's infiltration (Bicknell and others 2001, 2005) coupled with multiple surface and subsurface stores (interception storage, surface storage, upper zone soil storage, lower zone soil storage, active groundwater, and inactive [deep] groundwater). Individual land units within a sub-basin are represented using a hydrologic response unit (HRU) approach that combines an overlay of land cover, soil, and slope characteristics. The stream network links the surface runoff and groundwater flow contributions from each of the HRUs and routes them through water bodies. The stream model includes PPT and evaporation from the water surfaces as well as streamflow contributions from the watershed, tributaries, and upstream stream reaches.

SWAT—SWAT was developed to simulate the effect of land management practices on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land use, and management conditions over long periods of time (Neitsch and others 2005). SWAT requires data inputs for weather, soils, topography, vegetation, and land use to model water and sediment movement, nutrient cycling, and numerous other watershed processes. SWAT (as implemented here) uses the curve number approach (USDA Soil Conservation Service 1972) to estimate surface runoff and then completes the water balance through simulation of subsurface flows, evapotranspiration (ET), soil storages, and deep seepage losses at the daily time step. The curve number is estimated as a function of land use, cover, condition, hydrologic soil group, and antecedent soil moisture.

HSPF and SWAT for this application—For both models, the 20 larger watersheds were divided into a series of sub-basins at approximately the Hydrologic Unit Code (HUC) 10-digit scale, representing the drainage areas that contribute to each of the stream reaches. Both the HSPF and SWAT models used the 2001 National Land Cover Database (NLCD) (Homer and others 2007) to characterize the land surface. For HSPF, soils are distinguished on the basis of hydrologic soil group (HSG) as defined in State Soil Geographic (STATSGO) database (USDA NRCS

2012) soil coverages. The HRU definitions for SWAT in this application use the same land cover as HSPF but distinguish soils based on STATSGO's dominant soil classification, not just HSG. Withdrawals were included if they resulted in a modification of flow at downstream gauges on the order of 10 percent or more. Time series of observed PPT and air TEMP (hourly for HSPF, daily for SWAT) from 37 weather stations in the ACF Basin were obtained from the 2006 BASINS 4 Meteorological Database (USEPA 2008). Potential evapotranspiration (PET) for both HSPF and SWAT was computed using the Penman-Monteith energy balance method (Jensen and others 1990, Monteith 1965) using solar radiation, wind movement, cloud cover, and relative humidity estimated using the SWAT weather generator. A full energy balance approach was used because the focus of the study was to evaluate potential response to future climates, in which the relations between different energy inputs may change, even though a better calibration fit to current climate conditions can often be obtained using simpler temperature-based approaches when the energy inputs are subject to uncertainty.

The calibration objectives for both HSPF and SWAT were to achieve error statistics for total streamflow volume, seasonal streamflow volume, and high and low streamflow within recommended ranges (Donigian 2000, Lumb and others 1994) while also maximizing the Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe 1970). Because the objectives of this application focused at the large basin scale, calibration was undertaken only at the HUC 8-digit and larger watershed scale. For this application of HSPF, four model parameters were the primary focus during model calibration to improve model fit for hydrology: INFILT (index to mean soil infiltration rate), AGWRC (groundwater recession rate), LZSN (lower zone nominal soil moisture storage), and BASETP (ET by riparian vegetation). For SWAT, 11 model parameters were adjusted during model calibration to improve model fit in this application: curve number; SECO (soil evaporation compensation factor); SURLAG (surface runoff lag coefficient); groundwater "revap" rates, baseflow factor; GW_DELAY (groundwater delay time); GWQMN (threshold depth of water in the shallow aquifer required for return flow to occur); RevapMN (threshold depth of water in the shallow aquifer required for "revap" or percolation to the deep aquifer to occur); CANMAX (maximum canopy storage); Manning's "n" value for overland flow, main channels, and tributary channels; and Sol_AWC (available water capacity of the soil layer, mm water/mm of soil).

WaterFALL®

Research Triangle Institute's WaterFALL® system employs an updated version of a well-established hydrologic model, the Generalized Water Loading Function (GWLFL)

(Haith and Shoemaker 1987, Haith and others 1992) that has been modified to (1) run on the U.S. Environmental Protection Agency's enhanced National Hydrography Dataset (NHDPlus) hydrologic network, (2) accept parameterization from national datasets, and (3) include the impacts of human alterations on streamflows. WaterFALL® utilizes the hydrologic simulation within GWLF for each catchment of the NHDPlus network in the watershed of interest and then accumulates and moves water downstream with an embedded time-lagged routing routine, providing a distributed hydrologic model across the NHDPlus. Parameterization of WaterFALL® occurs through the geoprocessing of national datasets for land cover, soils, and climate (mean daily TEMP and PPT) to each NHDPlus catchment. Each land cover class in a catchment is characterized by the predominant HSG and predominant percent sand, silt, and clay for the underlying soil forming an HRU for runoff calculation within the catchment. Mean TEMP and PPT are quantified by catchment. Additional basin-specific characteristics such as water uses may also be indexed to each catchment from local data sources.

Like SWAT, surface runoff in WaterFALL® is computed on a daily basis using the curve number method across each land cover type in a catchment. Discharge from shallow groundwater is computed using a lumped parameter catchment-level water balance for unsaturated and shallow saturated zones controlled by the available water capacity (AWC) of the unsaturated zone, a recession coefficient (RCoeff) providing the rate of release from the saturated zone to the stream channel, and a first-order approximation of infiltration losses to deep aquifer storage simulated using a seepage coefficient (SEEP). The seepage release constitutes a loss from the system, where the water is no longer available to reach the stream in the temporal context of daily rainfall-runoff modeling. Daily ET from the unsaturated zone is computed using a land use-based cover factor and PET computed using the Hamon temperature-based method (Hamon 1963). Three model parameters (AWC, RCoeff, and SEEP) are adjusted during an automated calibration process using a customized version of the Parameter Estimation Tool (PEST). Because of the physical basis of the AWC and RCoeff parameters, a priori values for the parameters are indexed to individual catchments within the WaterFALL® database, and a multiplier across the physically based values is adjusted during calibration. The SEEP parameter is set through calibration and consideration of local conditions.

The application of WaterFALL® used for this study was developed to create a hydrologic foundation for detailed assessment of human and climate effects on stream and river flows, including the impacts of hydrologic alterations on aquatic habitats in the Southeastern United States

(SEUS) at the NHDPlus catchment scale (~1.0 km²) (Kendy and others 2011). For this study, climate inputs included daily PPT and TEMP from a 4- x 4-km national dataset obtained from the USDA (Di Luzio and others 2008), land cover was based on the baseline condition assessment represented by the USGS Geographic Information Retrieval and Analysis System (GIRAS) land cover (Price and others 2006), and soils data were obtained from the Soil Survey Geographic database (SSURGO) (https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053627). Although water system discharges and withdrawals were obtained from State databases on public and non-public systems for other scenarios in the SEUS study, the WaterFALL® model simulations contributing to this study were unaltered by humans. WaterFALL® was calibrated at several USGS gauge locations in the study area for periods in the 1970s, commensurate with the land use coverage used to simulate a less-altered baseline for the SEUS study. Although performance was validated with later periods, some differentiation from the other models is expected where the calibration period more closely matched the period of this study. The three model calibration parameters (AWC, RCoeff, and SEEP) were optimized to minimize the differences in log-transformed daily flows, giving equal weight to differences in streamflows at the low and high end of the hydrograph.

WaSSI

The WaSSI model was developed by the Forest Service to assess the effects of climate change, land use change, and population growth on water supply stress, river flows, and aquatic ecosystems across the conterminous United States (Caldwell and others 2012, Sun and others 2011b). WaSSI has been successfully used in climate change assessments in the Eastern United States (Lockaby and others 2011, Marion and others 2013, Sun and others 2013, Tavernia and others 2013) and for examining the nexus of water and energy at the national scale (Averyt and others 2011, 2013). WaSSI is an integrated monthly water balance and flow routing model that simulates the full hydrologic cycle for each of 10 land cover classes at the 12-digit Hydrologic Unit Code (HUC) scale. The 10 land cover classes are aggregated from the 17 classes of the 2006 NLCD (Fry and others 2011). Infiltration, surface runoff, soil moisture, and baseflow processes for each HUC watershed's land cover were computed using algorithms of the Sacramento Soil Moisture Accounting Model (SAC-SMA) (Burnash 1995, Burnash and others 1973). STATSGO databases (USDA NRCS 2012) were used to compute the 11 SAC-SMA soil input parameters (Koren and others 2003). Monthly ET was modeled with an empirical equation derived from multisite eddy covariance ET measurements (Sun and others 2011a, 2011b). Required data to estimate ET included monthly mean Moderate Resolution Imaging

Spectroradiometer (MODIS) MOD15A2 leaf area index (LAI) (Zhao and others 2005), Hamon PET calculated as a function of TEMP and latitude (Hamon 1963), and PPT. This estimate of ET was then constrained by the soil water content computed by the SAC-SMA algorithm during extreme water-limited conditions. Monthly PPT and air TEMP inputs were based on Precipitation Elevation Regression on Independent Slopes Model (PRISM) estimates (PRISM Climate Group 2013). All water balance components were computed independently for each land cover class within each HUC watershed and accumulated to estimate the totals for the watershed. For the NLCD-based impervious cover fraction, storage and ET were assumed to be negligible, and thus all PPT falling on the impervious portion of a watershed for a given month was assumed to generate surface runoff in the same month and was routed directly to the watershed outlet. No anthropogenic water use was included, and the model was run using off-the-shelf input datasets without calibration.

Runoff Sensitivity to Changes in Climate

We quantified and compared changes in flow predictions at the study site under eight hypothetical climate change scenarios (table 4.2). Climate scenarios included:

- (1) increase PPT 10 percent, (2) decrease PPT 10 percent, (3) increase PPT 20 percent, (4) decrease PPT 20 percent, (5) increase TEMP 1 °C, (6) increase TEMP 2 °C, (7) increase PPT 10 percent and increase TEMP 2 °C, and (8) decrease PPT 10 percent and increase TEMP 2 °C.

These climate change scenarios are hypothetical; however, they are reasonable projections of potential long-term changes in PPT and TEMP in the SEUS by the middle of the 21st century derived from General Circulation Models (Walsh and others 2014) or were designed to represent extremes in dry (e.g., 20 percent decrease in PPT) or wet (e.g., 20 percent increase in PPT) years. For each scenario, PPT and/or TEMP were adjusted uniformly by the specified amount at each time step. Predicted annual and seasonal flows for each scenario were compared to the baseline climate scenario to quantify changes in flow resulting from the hypothetical change in climate. The slope of the linear relation between the relative change in runoff and the relative change in PPT was computed, representing the sensitivity of runoff to changes in PPT or the climate elasticity of streamflow (Sankarasubramanian and Vogel 2001). This metric has been successfully used in several other assessments evaluating the influence of climate change on runoff (Jha and others 2006, Legesse and others 2010, Mengistu and Sorteberg 2012).

RESULTS

Predicted changes in mean annual runoff at the study site using the large-scale, uncalibrated WaSSI model were similar to those of the fine-scale, calibrated HSPF and WaterFALL[®] models under many of the hypothetical

climate change scenarios considered (fig. 4.2). For example, under a climate scenario of a 10-percent reduction in PPT, the change in runoff among HSPF, WaterFALL[®], and WaSSI was -18.8, -18.0, and -21.3 percent, respectively. Under the more extreme changes in PPT (e.g., 20-percent decrease), WaSSI's predicted change in runoff (-41.8 percent) was slightly higher than that predicted by HSPF (-36.0 percent) and WaterFALL[®] (-34.5 percent). Predicted changes in runoff for scenarios of TEMP change were lower than those for changes in PPT, but HSPF, WaterFALL[®], and WaSSI models generally agreed on the magnitude of change. For example, under TEMP changes of 2 °C, the change in runoff was -4.9, -7.2, and -8.0 percent among HSPF, WaterFALL[®], and WaSSI, respectively. The SWAT model was generally more sensitive to changes in PPT and TEMP than the other models.

The sensitivity of mean annual runoff to changes in PPT, or climate elasticity of streamflow, was similar among the HSPF, WaterFALL[®] and WaSSI models. The SWAT model, however, appeared to be more sensitive to both increases and decreases in PPT than the other models (fig. 4.3). Under increasing PPT scenarios, WaSSI (slope = 2.2) had similar sensitivity to that of HSPF (slope = 2.1), but both were slightly more sensitive than WaterFALL[®] (slope = 1.9). Under decreasing PPT scenarios, WaSSI (slope = 2.1) appeared to be somewhat more sensitive than HSPF (slope = 1.8) and WaterFALL[®] (1.7).

Inspection of changes in monthly mean runoff as a result of a 20-percent decrease in PPT reveals that while changes in mean annual runoff were similar among some models, changes in monthly mean runoff were quite variable at this site (fig. 4.4). WaSSI and SWAT models were most sensitive to changes in PPT during the winter months

Table 4.2—Climate scenarios used to evaluate sensitivity of predicted runoff to climate change

Scenario ^a	Identifier	PPT change	TEMP change
1	PPT +10%	+10%	No change
2	PPT -10%	-10%	No change
3	PPT +20%	+20%	No change
4	PPT -20%	-20%	No change
5	TEMP +1	No change	+1 °C
6	TEMP +2	No change	+2 °C
7	PPT +10%, TEMP +2	+10%	+2 °C
8	PPT -10%, TEMP +2	-10%	+2 °C

^a For all scenarios, precipitation (PPT) and temperature (TEMP) were adjusted by the amount shown at each time step relative to the historical baseline period from 1980–1999.

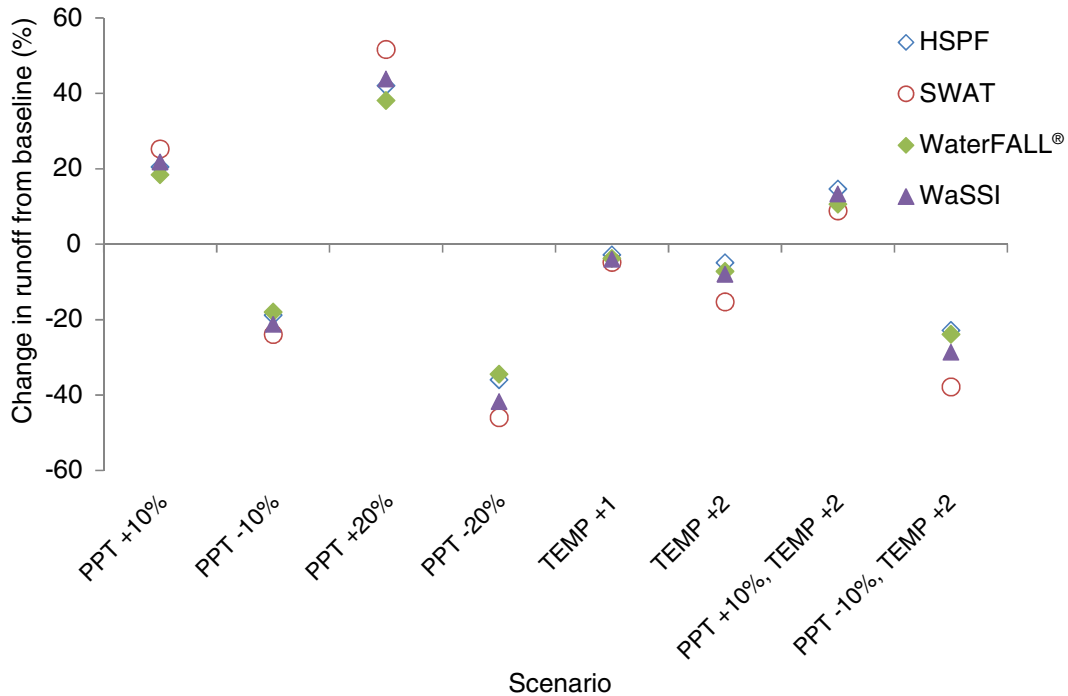


Figure 4.2—Predicted relative change in mean annual runoff for the Flint River study site based on the eight hypothetical climate change scenarios. [See table 4.1 for hydrologic model definitions; see table 4.2 for climate change scenario descriptions.]

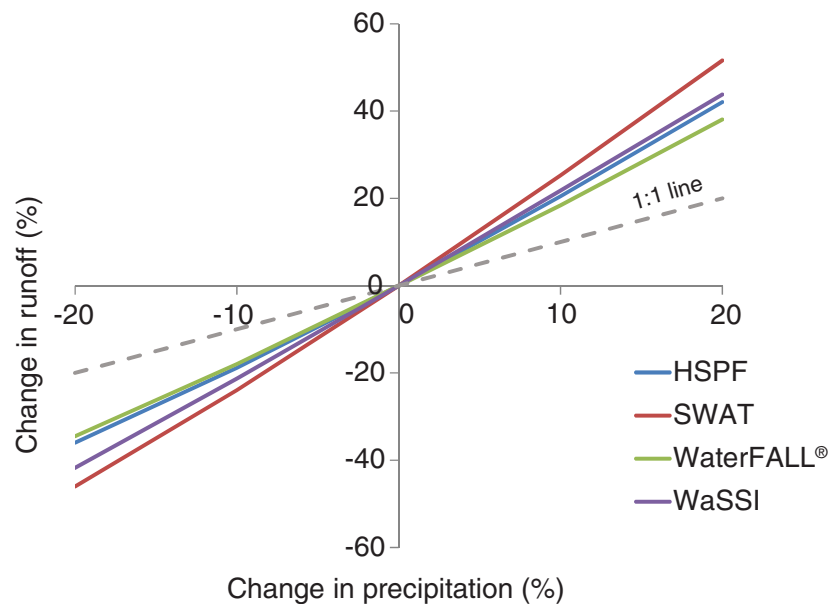


Figure 4.3—Predicted change in mean annual runoff for various changes in precipitation. The slope of the linear relationship between change in runoff and change in precipitation represents the sensitivity of runoff to precipitation change. The dotted line represents the 1:1 line, and the slopes of the modeled output for HSPF, SWAT, WaterFALL®, and WaSSI would fall directly on the 1:1 line if the change in runoff were equal to the change in precipitation. [See table 4.1 for hydrologic model definitions.]

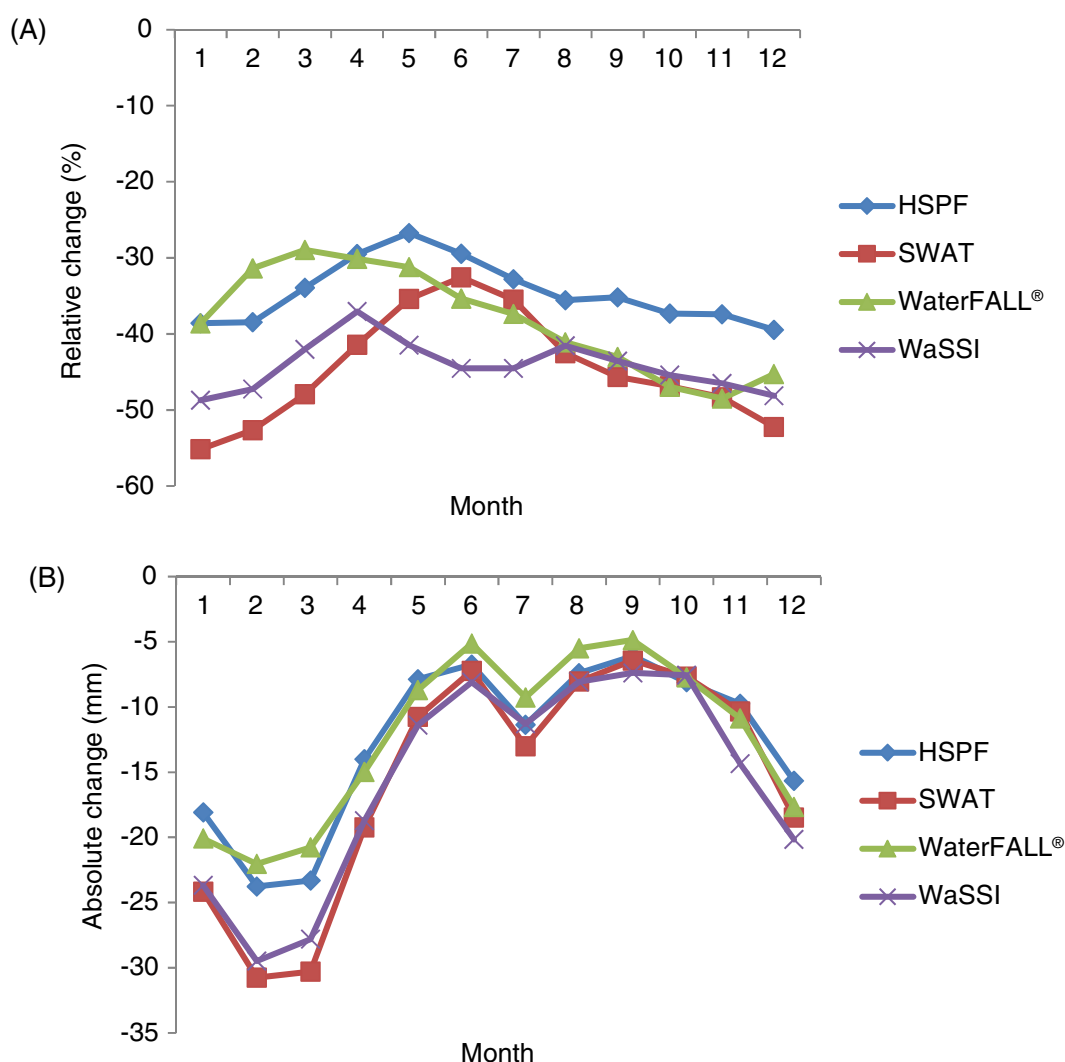


Figure 4.4—Relative (A) and absolute (B) changes in monthly mean runoff for a 20-percent precipitation decrease. [See table 4.1 for hydrologic model definitions.]

when runoff is highest, which likely explains why they are more sensitive to PPT decreases at the mean annual scale than HSPF or WaterFALL®. For example, mean relative changes in runoff in February were 47.3 and 52.6 percent for WaSSI and SWAT, respectively, while changes in February runoff for HSPF and WaterFALL® were 38 and 31 percent, respectively.

These differences in sensitivity of runoff to changes in PPT across months are related to the differences in seasonality of ET and soil moisture storage among models (fig. 4.5). While PPT was similar for all models, WaSSI and SWAT predicted higher ET rates during the winter months (November, December, and January) than did HSPF and WaterFALL®. Thus, reductions in PPT in the climate change scenarios during the winter months may impact runoff more than ET for WaSSI and SWAT because

less excess water would be available to generate runoff due to the higher winter ET rates. WaterFALL® predicted the lowest winter ET rates, resulting in the highest winter runoff rates among models.

DISCUSSION

Large- and fine-scale hydrologic models could be used in combination to identify specific areas of concern across large regions and to provide high-resolution quantitative estimates of changes in water supply ERFMs in these areas under changes in climate, but the differences in predicted streamflow response across large- and fine-scale models must be assessed before applying such a multi-scale modeling approach. The goal of this study was to examine the potential for combined application of large- and fine-scale hydrologic modeling approaches over large regions for climate change assessment studies. We

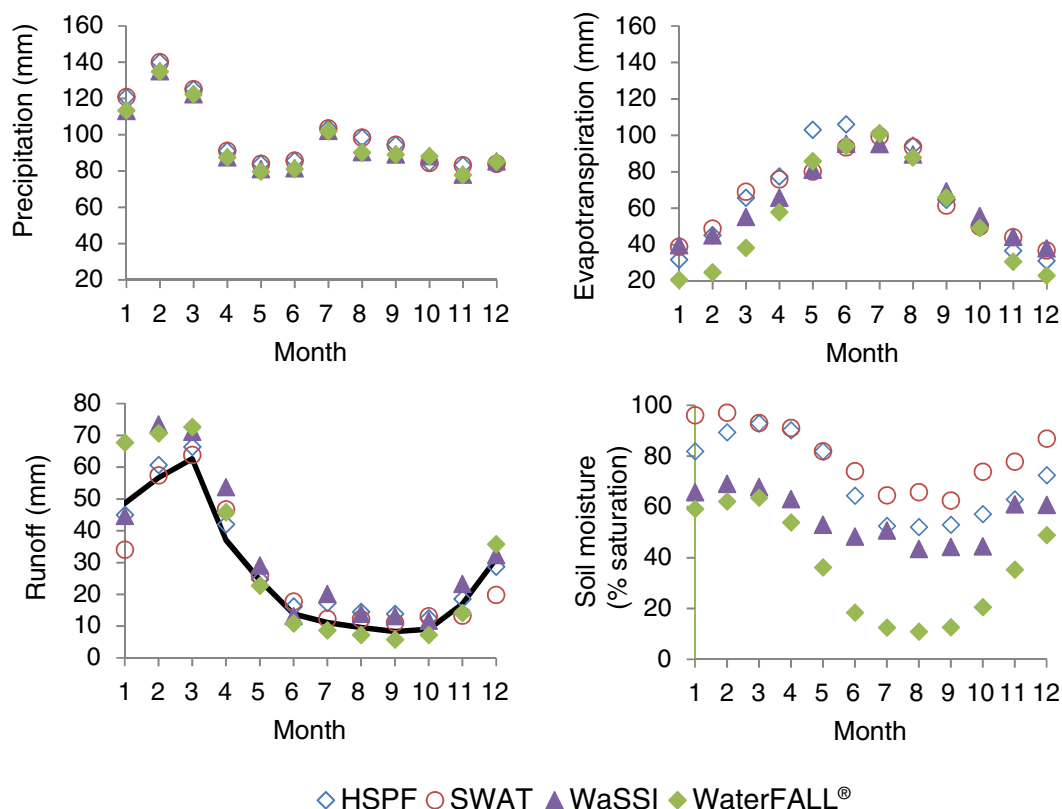


Figure 4.5—Monthly median precipitation, evapotranspiration, soil moisture, and runoff for all models under baseline conditions. [See table 4.1 for hydrologic model definitions.]

quantified differences in sensitivity of predicted runoff to climate change (i.e., PPT and TEMP) among one large-scale (WaSSI) and three fine-scale (HSPF, SWAT, and WaterFALL®) hydrologic models.

While the absolute magnitude of model-predicted runoff sensitivity to changes in PPT and TEMP may differ, the general pattern of the results of this study are consistent with previous work. Tang and others (2012) found that annual mean streamflow in the Salmon River Basin, ID, decreased 2–6 percent across sub-watersheds in the basin for a TEMP increase of 2 °C using the Variable Infiltration Capacity (VIC) model. Legesse and others (2010) used PRMS to evaluate the effect of changes in PPT and TEMP on runoff in the Meki River, Ethiopia, and found that runoff was more sensitive to increases in PPT (+80 percent for +20 percent PPT) than decreases (-62 percent for -20 percent PPT), and a 1.5 °C increase in TEMP resulted in a 13-percent decrease in runoff. Mengistu and others (2012) used the SWAT model to evaluate changes in annual runoff in the Eastern Nile Basin and found that runoff increased 10–35 percent for a 10-percent increase in PPT, decreased 17–26 percent for a 10-percent decrease in PPT, and decreased up to 6 percent for a 2 °C increase in TEMP across three sub-watersheds in the basin. Jha and

others (2006) used SWAT to evaluate sensitivity to PPT changes in the Upper Mississippi River Basin and found a 26-percent reduction and 28-percent increase in runoff for 10-percent decreases and increases in PPT, respectively.

Results of this study suggest that runoff predicted by large-scale models (e.g., WaSSI) and fine-scale models (e.g., HSPF), despite differences in model structure and level of calibration, is similar in sensitivity to changes in PPT and TEMP at the annual scale (figs. 4.2 and 4.3). Annual runoff sensitivity for increases in PPT at the Flint River study site ranged from 1.9 to 2.2 among the HSPF, WaterFALL®, and WaSSI models, and sensitivity for decreases in PPT ranged from 1.8 to 2.1. These values are well within the range of streamflow elasticity to climate reported for the SEUS (Sankarasubramanian and Vogel 2001). Although there was generally good agreement in sensitivity of runoff to changes in PPT among models at the annual scale, there were differences in predicted sensitivity among models at the monthly scale (fig. 4.5). For example, under a scenario of a 20-percent decrease in PPT, the predicted change in March runoff was -33.9, -47.9, -28.9, and -42.0 percent for HSPF, SWAT, WaterFALL®, and WaSSI, respectively (fig. 4.4a). The combination of differences in model structure (e.g., ET calculation method), parameterization (e.g., land

cover characteristics), and calibration strategy evidently influences model predictions at the monthly scale. Further study is necessary to tease out the root cause of the differences in runoff sensitivity. While large- and fine-scale models have similar predictive performance at the monthly time step, in light of these findings caution should be used when combining large- and fine-scale models for regional resource management applications at time scales other than the long-term annual scale.

LIMITATIONS

While this study provided unique insights into differences in predicted runoff sensitivity to climate among models, it is not a comprehensive assessment taking into account all of the factors that could influence these relationships. Some limitations of this study include:

1. Only a subset of the hydrologic models evaluated elsewhere in this report were considered in this study. Models included here consisted of those from government agencies and private organizations that were able to simulate the additional climate scenarios.
2. The models evaluated were not developed using the same calibration objective functions and input datasets. It is not known how these differences in model calibration strategy may affect predicted runoff sensitivity to changes in PPT and TEMP.
3. Models evaluated were applied to a single basin in the SEUS region. The relative differences in predicted runoff sensitivity to changes in PPT and TEMP may vary in other hydroclimatic settings.
4. In general, hydrologic model streamflow predictions are subject to uncertainty in climate, land cover, soil, and LAI input data, as well as uncertainty in the representation of the physical processes that govern streamflow magnitude and timing.

CONCLUSIONS

The objective of this study was to examine the potential for combining large- and fine-scale hydrologic modeling approaches over large regions for climate change assessment studies. We compared the sensitivity of runoff predictions from one large-scale and three fine-scale models to changes in PPT and TEMP and found that, while there were differences in model complexity and calibration strategy, predicted changes in runoff to changes in climate were similar at the long-term annual scale, but there were differences in predicted sensitivity among models at the monthly scale. Due to these seasonal differences, caution should be used when combining large- and fine-scale models for regional resource management applications at time scales other than the long-term annual scale. Future research is needed to understand the differences in predicted change in monthly runoff and to investigate the effect of model calibration strategy, as well as to evaluate differences in predicted runoff sensitivity across a larger set of gauged watersheds. Despite these limitations, the results of this study show promise in the potential to use a combination of large- and fine-scale models to examine climate change effects on regional water resources.

CHAPTER 5

Using Regional-Scale Flow-Ecology Modeling to Identify Catchments Where Fish Assemblages are Most Vulnerable to Changes in Water Availability

INTRODUCTION

Environmental water studies over the last 2 decades have emphasized the inherent linkage and, in some cases, the tension between maintaining water for human use as well as for ecosystem needs (Acreman and others 2008, Kendy and others 2012, Poff and others 2010, Shenton and others 2012). Considerable emphasis has been placed on understanding the broad discharge patterns that influence the structural, functional, and life history strategies of biotic communities (Bunn and Arthinton 2002, Mims and Olden 2012, Naiman and others 2008). More recently, there has been an emphasis on developing hydrologic indices for characterizing the flow regime (Henriksen and others 2006, Monk and others 2007, Worrall and others 2014), systematically arranging streams and rivers into specific stream classes with respect to flow regime characteristics (Archfield and others 2013; Kennard and others 2010; Kennen and others 2007, 2009; McManamay and others 2012; Olden and Poff 2003), and building flow-ecology response models that link changes in streamflow and water availability to changes in assemblage structure and function (e.g., Arthington and others 2014; Chessman and others 2010; Freeman and others 2013; Kennen and others 2010, 2014; McManamay and others 2013; Stewart-Koster and others 2014; Turner and Stewardson 2014). All of these studies emphasize the identification of the streamflow components needed to help determine ecological and environmental endpoints and the inherent linkages between changes in streamflow processes and ecosystem response.

Changes in riparian and watershed-scale land use and associated alterations in stream habitat and streamflow processes have been linked to declines in native stream fish populations (Olden 2016) and a general downward trend in aquatic biodiversity across the globe (Dudgeon and others 2006, Vörösmarty and others 2010). While minimizing impervious surfaces and maximizing the conservation of contiguous tracts of forested lands in watersheds support the preservation of stream fish populations (Kennen and others 2005), alterations in water availability, including impoundments, streamflow regulation, and water resource

development, which are essential to meet the water needs of a growing population, are strongly linked to changes in native fish diversity, abundance, and resilience (Conroy and others 2003, Poff and Zimmerman 2010, Warren and others 2000). Confounding the effects of land use change and streamflow alteration are projected increases in drought frequency and duration associated with climate change (IPCC 2013, Melillo and others 2014), which can place further stress on water supplies and fish assemblage structure (Keaton and others 2005, Matthews and Marsh-Matthews 2003, White and others 2016). Understanding these linkages and the potential effect of changes in water availability on aquatic ecosystems is critical for long-term water management in areas facing significant water stress, especially when the needs of humans and aquatic ecosystems appear to conflict and sometimes result in legal proceedings. This is periodically the case in the Southeastern United States (SEUS) where water stress is known to occur in conjunction with drought cycles (e.g., Seager and others 2009). It is under these conditions that water managers must identify areas of concern and make informed decisions about water conservation that affect human and ecological use in these areas. Unfortunately, there is a lack of decision-support tools that identify areas of concern across broad regions, especially tools with a spatial resolution relevant to management decision making.

The primary objective of this study was to demonstrate the efficacy of using relatively simple, large-scale hydrologic models in conjunction with ecological data to develop empirical flow-ecology response models that predict the effect of changes in water availability on fish species richness (FSR), an easily quantified assemblage metric. Additionally, we sought to use this modeling approach to identify catchments or “hot spots” of FSR change under a plausible set of future land use, climate, and withdrawal change scenarios and test the hypothesis that FSR in the North Carolina Piedmont will decrease with predicted increases in urban land use (i.e., impervious surfaces), changes in climate, and increases in water withdrawals (see Hain and others 2018).

METHODS

Study Area

We focused on catchments in the Piedmont ecoregion of North Carolina to develop empirical relationships between streamflow and FSR (fig. 5.1A). Seven major river basins are partially located within the Piedmont region. These include the Broad (BRD), Cape Fear (CPF), Catawba (CTB), Neuse (NEU), Roanoke (ROA), Tar-Pamlico (TAR), and Yadkin (YAD) River Basins (fig. 5.1B). The North Carolina Piedmont contains or intersects 886 12-digit Hydrological Unit Code catchments (hereafter HUC-12s) identified by the U.S. Department of Agriculture (USDA) Natural Resources Conservation Service's (NRCS) Watershed Boundary Dataset Geographic Information System (GIS) layer. North Carolina has one of the highest rates of population growth in the United States and is now among the top 10 most populous States (U.S. Census Bureau 2016). Much of this growth has occurred in the Piedmont, which contains many of the State's most rapidly growing cities (i.e., Charlotte, Durham, Raleigh, and Winston-Salem) (fig. 5.1A).

The Piedmont region of North Carolina (fig. 5.1A) has a humid subtropical climate of warm summers and cool, moist winters. The region receives, on average, 107–117 cm year⁻¹ of precipitation (PPT) (North Carolina Climate Office 2016) and is made up of gently rolling forested hills, with elevations ranging from 60 to 470 m. The geology of the Piedmont is dominated by metamorphic (gneisses and schist) and igneous (granite, diorite, and gabbro) rocks overlain by “clayey” ultisols (soils with light upper layers and a reddish sub-soil) that were mainly formed through physical weathering and alluvial processes. These soils are rich in aluminum and silicates and contain eroded sediments mixed with organic material. Natural vegetative cover in this region consists mainly of mesic mixed hardwoods (e.g., American beech [*Fagus grandifolia*], tulip poplar [*Liriodendron tulipifera*], hickory [*Carya* spp.], and red and white oak [*Quercus* spp.]), though wetlands occur in some lower elevations, and patches of pine (*Pinus* spp.) forests are found in more xeric regions. Population growth and development in the North Carolina Piedmont have altered the natural landscape and increased water demand. Surface water and groundwater withdrawals have reduced baseflow, and estimates of water use show that, in 2010, the total gross fresh surface water withdrawals across the 54 counties in the region amounted to 11.7 billion m³ year⁻¹ (Maupin and others 2014).

Modeling Approach

For this study, we implemented a multi-step modeling approach (fig. 5.2). First, FSR was calculated for 385 distinct fish sampling sites in the North Carolina Piedmont using data collected by the North Carolina Division of

Water Resources (NCDWR). Average monthly streamflow for the sites was then predicted using the well-documented Water Supply Stress Index (WaSSI) model (Caldwell and others 2015). Fish species richness and streamflow predictions were used to build a boosted regression tree (BRT) flow-ecology model, which was used to predict the relationship between a subset of ecologically relevant flow metrics (ERFMs) and FSR in all HUC-12s in the North Carolina Piedmont. The results of the model were then used to predict FSR under three plausible scenarios of future water withdrawals, climate change, and increases in impervious surfaces. Finally, a “hot spot” analysis was used to identify individual HUC-12s that were most likely to be affected by changes in water availability.

Biological Data Aggregation

The Biological Assessment Unit (BAU) of the NCDWR began sampling each of the State's 17 river basins on a 5-year rotation in 1990 (NCDENR 2006). Streams wadeable from shoreline to shoreline were sampled by the Stream Fish Community Assessment Program for an average distance of 183 m (600 feet). A four-person team collected all fish at each site using a modified two-pass depletion technique with two backpack electrofishing units and two persons netting. All fish were identified to species, enumerated, inspected for disease and deformities, and measured for total length before being released back into the stream. Specimens not easily identified in the field were preserved in 10-percent formalin and transported to the BAU laboratory in Raleigh, NC. Between 1990 and 2012, 967 sampling events were performed by BAU at 385 unique sampling stations in the North Carolina Piedmont region. The sampling time window was limited to the spring between April and June which helped control for seasonal variability in flow conditions and was important for maintaining a consistent dataset for analysis across samples. Where unique stations were sampled multiple times, measures of FSR were averaged across all sampling events, resulting in a final sample size of 385 for developing flow-ecology relationships.

Upstream contributing catchments were delineated for each of the 385 unique NCDWR sampling stations (fig. 5.1B). Delineations were performed using Arc Hydro tools in ArcGIS 10.1 using digital elevation models procured from the North Carolina Floodplain Mapping Program (NC Floodplain Mapping Program 2013).

Streamflow Prediction

Streamflow was predicted for all study catchments using the WaSSI model, which was developed by the USDA Forest Service to assess the effects of climate change, land use change, and population growth on water supply stress, river flows, and aquatic ecosystems across the conterminous United States (Caldwell and others 2012,

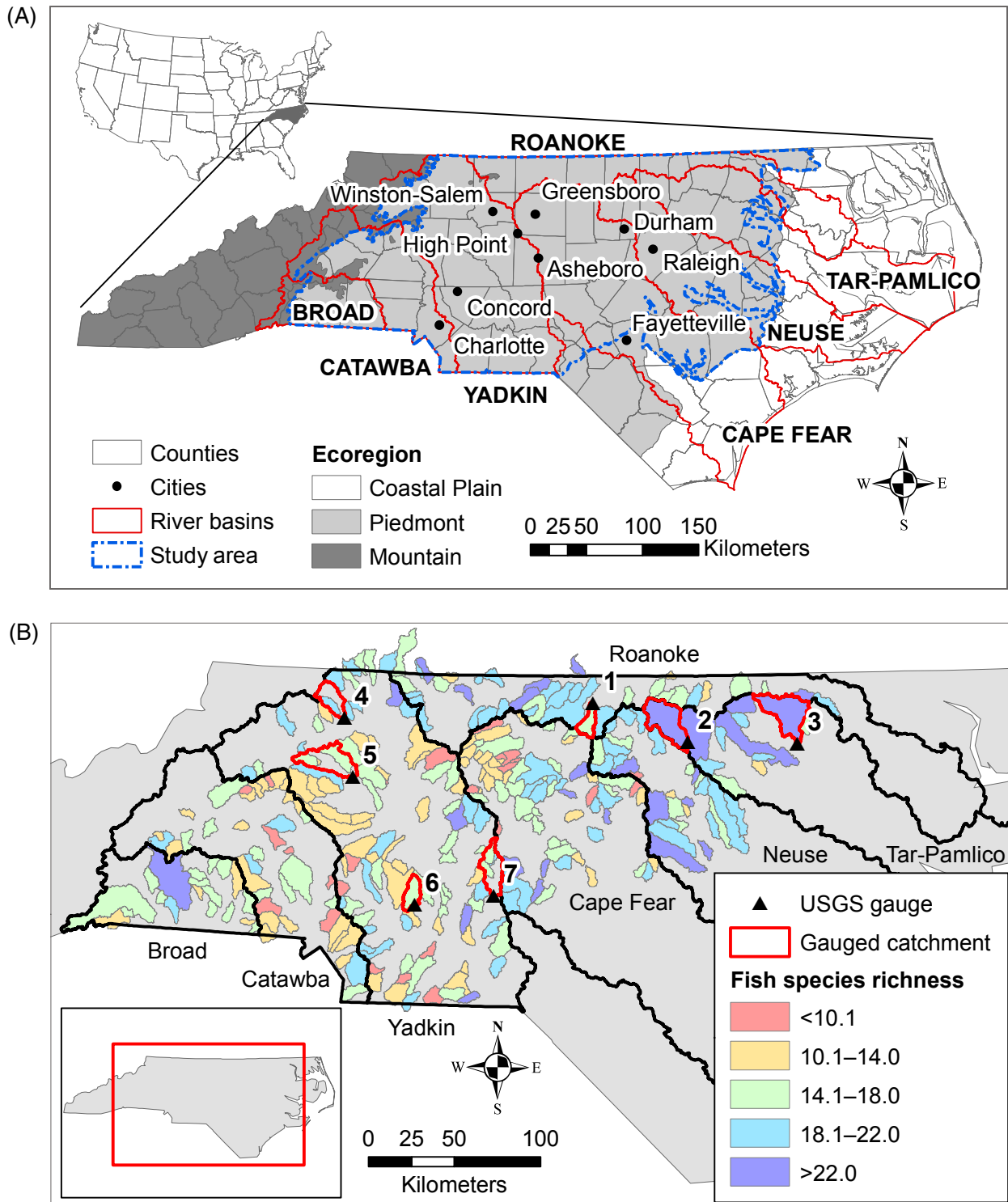


Figure 5.1—Map of North Carolina showing the study area spanning the Piedmont ecoregion, as well as parts of the Mountain and Coastal Plain ecoregions (A), and the range in FSR values for the BRT model training dataset in the North Carolina Piedmont and locations of seven USGS reference gauges used for the WaSSI model validation (B). Study area extent was chosen based on best professional judgement and discussions with NCDWR personnel (A). Each colored polygon in (B) represents the delineated contributing watershed for each ecological sample site.

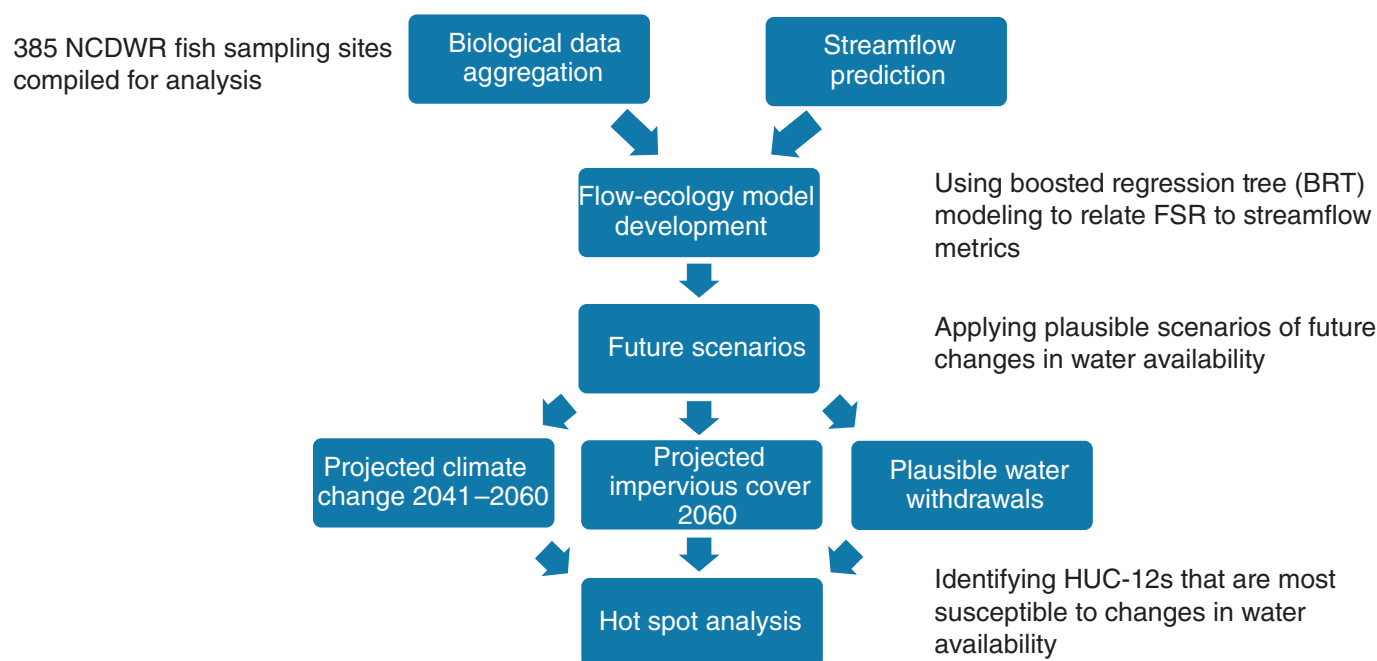


Figure 5.2—Study modeling approach. Biological data were aggregated from NCDWR stream community assessment data. Streamflow was predicted using the WaSSI model.

2015, Sun and others 2011b). WaSSI has been successfully used in climate change assessments in the Eastern United States (Lockaby and others 2011, Marion and others 2013, Sun and others 2013, Tavernia and others 2013) and for examining the nexus of water and energy at the national scale (Averyt and others 2011, 2013). WaSSI is an integrated monthly water balance and flow routing model that simulates the full hydrologic cycle for each of 10 land cover classes at the HUC-12 scale. The 10 land cover classes are aggregated from the 17 classes of the 2006 National Land Cover Database (NLCD) (Fry and others 2011). Infiltration, surface runoff, soil moisture, and baseflow processes for each HUC-12 catchment land cover class were computed using algorithms of the Sacramento Soil Moisture Accounting Model (SAC-SMA) (Burnash 1995, Burnash and others 1973). State Soil Geographic (STATSGO) databases (USDA NRCS 2012) were used to compute the 11 SAC-SMA soil input parameters (Koren and others 2003). Monthly evapotranspiration (ET) was modeled with an empirical equation derived from multisite eddy covariance ET measurements (Sun and others 2011a). Required data to estimate ET included monthly mean Moderate Resolution Imaging Spectroradiometer (MODIS) MOD15A2 leaf area index (LAI) (Zhao and others 2005), potential ET (PET) calculated as a function of air temperature (TEMP) and latitude (Hamon 1963), and PPT. This estimate of ET was then constrained by the soil water content computed by the SAC-SMA algorithm during extreme water-limited conditions. Monthly PPT and TEMP inputs were based on Parameter-elevation Relationships on Independent Slopes Model (PRISM)

estimates (PRISM Climate Group 2013). All water balance components were computed independently for each land cover class within each catchment and accumulated to estimate the totals for the catchment. For the NLCD-based impervious cover fraction, storage and ET were assumed to be negligible, and thus all PPT falling on the impervious portion of a catchment for a given month was assumed to generate surface runoff in the same month and was routed directly to the catchment outlet.

Although the WaSSI model can be calibrated, no calibration of model input parameters was performed for this study. WaSSI was developed to include the key ecohydrological processes that affect the water balance with off-the-shelf input datasets while having an acceptable level of predictive performance without calibration. In doing so, the model is not subject to the complexities and uncertainties associated with transferring model parameters from calibrated to ungauged catchments (Siviplan and others 2003) and using the model to assess the effect of climate or land cover scenarios outside of the conditions for which the model is calibrated. Despite being uncalibrated, WaSSI has been found to have similar predictive performance at the monthly time step to other calibrated, process-based models (Caldwell and others 2015).

Streamflow was predicted using the monthly WaSSI output from the years 1991–2010. This output represented the average streamflow for each month of the year over the 20-year period and resulted in 12 average monthly streamflow

values for each site. We calculated a suite of ERFMs from these monthly averages targeting flow metrics that account for the magnitude and seasonality (timing) of streamflow (Poff and others 1997) in an effort to capture flow signals important to fish life history. This included minimum monthly streamflow in $\text{m}^3 \text{s}^{-1}$ (low flow; MinCMS); maximum monthly streamflow (high flow; MaxCMS); average monthly streamflow (average flow; AveCMS); average streamflow for April, May, and June (spring flow; AMJCMS); average streamflow for August (summer flow; AugCMS); and a measure of the coefficient of monthly streamflow variability (FloVar). FloVar was computed by dividing the standard deviation of the decreased monthly flow values by the original monthly mean streamflow. This measure of streamflow variability is equivalent to “MA39,” a common measure of monthly streamflow variability presented in Olden and Poff (2003) and Henriksen and others (2006). Additionally, the proportion of surface flow coming from impervious surfaces (QFRAC_IMP) was estimated for each catchment. All statistics were estimated for contributing catchments to each NCDWR sample site, as well as all HUC-12s in the North Carolina Piedmont. The monthly time step allows us to evaluate the ability of large-scale, easily parameterized models to provide flow information that is useful for determining changes in ecosystem integrity.

We validated the WaSSI model flow predictions by computing classical hydrologic model fit statistics as

well as the prediction of ERFMs at seven USGS gauges located in the study area (table 5.1, fig. 5.1B). Gauges identified as reference sites in the USGS Gages II database (Falcone 2011, Falcone and others 2010) were selected for validation procedures and were either co-located with a fish training site or had one or more fish training sites anywhere within the gauged basin. Classical fit statistics evaluated included bias in mean streamflow, the Nash-Sutcliffe Efficiency (NSE) statistic (Nash and Sutcliffe 1970), the root mean squared error (RMSE), and the coefficient of determination (R^2). Ecologically relevant flow metrics evaluated included MaxCMS and FloVar that were used in the four-variable flow-ecology model (described below). Bias in mean streamflow within ± 25 , ± 15 , and ± 10 percent was considered indicative of satisfactory, good, and very good hydrologic model performance, respectively (Moriassi and others 2007). Similarly, NSE values that are >0.50 , >0.65 , and >0.75 for prediction of monthly streamflow were considered to be indicative of satisfactory, good, and very good model performance, respectively (Moriassi and others 2007). The NSE can range from negative infinity to 1.0; the closer NSE is to 1.0, the better the model fit. Negative values of NSE indicate that using the mean of the observations provides a better fit than the model. A hydrologic uncertainty of ± 30 percent was used to aid in placing model prediction bias of ERFMs into context with inherent variability in streamflow and flow measurement (Murphy and others 2013).

Table 5.1—Summary of classical hydrological model fit statistics and bias in prediction of the ecologically relevant flow metrics^a (ERFMs) used in the four-variable boosted regression tree (BRT) model across the seven USGS gauges used for WaSSI model validation

Site	Gauge	Description	Drainage area (km^2)	Classical model fit statistics				ERFMs	
				Bias in mean streamflow (%)	NSE	RMSE ($\text{m}^3 \text{s}^{-1}$ [cms])	R^2	Bias in MaxCMS (%)	Bias in FloVar (%)
1	02077200	Hyco Creek Near Leasburg, NC	121.7	16	0.60	0.85	0.63	-12	-26
2	02081500	Tar River near Tar River, NC	428.4	16	0.74	2.05	0.76	-17	-34
3	02082950	Little Fishing Creek near White Oak, NC	460.9	10	0.78	2.01	0.79	-17	-44
4	02112360	Mitchell River near State Road, NC	205.3	-10	0.50	1.17	0.70	2.4	73
5	02118500	Hunting Creek near Harmony, NC	400.5	13	0.60	2.30	0.69	3.4	3.7
6	02125000	Big Bear Creek near Richfield, NC	144.5	6.9	0.81	0.76	0.81	-11	-18
7	02128000	Little River near Star, NC	273.5	-8.3	0.71	1.45	0.72	-16	0.8
Mean (standard deviation)			290.7 (140.0)	6.2 (11.0)	0.68 (0.11)	1.51 (0.62)	0.73 (0.06)	-9.5 (8.9)	-6.4 (39.1)

^a Bias in mean streamflow within ± 25 , ± 15 , and ± 10 percent is considered indicative of satisfactory, good, and very good hydrological model performance, respectively, while Nash-Sutcliffe efficiency (NSE) values that are >0.50 , >0.65 , and >0.75 for prediction of monthly streamflow are considered to be indicative of satisfactory, good, and very good model performance, respectively. A hydrologic uncertainty of ± 30 percent was used to aid in placing model prediction bias of ERFMs into context with inherent variability in streamflow and flow measurement (Murphy and others 2013).

FloVar = coefficient of monthly streamflow variability; MaxCMS = maximum monthly streamflow in $\text{m}^3 \text{s}^{-1}$ (cms); NSE = Nash-Sutcliffe Efficiency; R^2 = coefficient of determination; RMSE = root mean squared error.

Flow-Ecology Model Development

We developed a FSR BRT model using observed biological data and WaSSI streamflow predictions for all 385 NCDWR sample sites in the training dataset. Boosted regression tree models are only briefly described here as their use and technical details (e.g., Breiman and others 1984, De'ath and Fabricius 2000, Prasad and others 2006) as well as application (Aertsen and others 2010; Brown and others 2012; Clapcott and others 2011; Elith and others 2008; Leclerc and others 2011; Waite and others 2010, 2012) have been widely presented in the literature. Boosted regression trees are part of the classification and regression tree (CART) or decision tree family, a family of techniques used to advance single classification or regression trees by averaging the results for each binary split from numerous trees or forests. The objective of BRT models is to reduce the predictive error and improve overall performance (De'ath 2007, Elith and others 2008). In BRT, after the initial tree has been developed, successive trees are grown on reweighted versions of the data, giving more weight to cases that are incorrectly classified than those that are correctly classified within each growth sequence (Waite and others 2012). As more and more trees are grown in BRT, the large number of trees increases the chance that cases that are difficult to classify initially are correctly classified, thus representing an improvement to the basic averaging algorithm used in random forest (De'ath 2007). Boosted trees and random forest models retain the positive aspects of single trees seen in CART models, yet have improved predictive performance, can easily assess nonlinearities and interactions, and can provide an ordered list of the importance of the explanatory variables (De'ath 2007, Leclerc and others 2011).

Although BRT offers improved modeling performance over CART, the simple single tree obtained from CART is lost, making visualization of the results more difficult. Partial dependency plots (PDPs) provide a way to visualize the effect of a specific explanatory variable on the response variable after accounting for the average effects of all other explanatory variables (De'ath 2007, Elith and others 2008); PDPs for selected variables important in models appear as examples in the results. Boosted regression tree models were run using the *gbm* library in R and specific code from Elith and others (2008).

Boosted regression tree models were developed using FSR as the response variable and ERFMs and river basin as explanatory variables. We developed the BRT models using the training dataset (fig. 5.1B) with a bag fraction of 0.5, a learning rate of 0.004, and a tree complexity of 3. A bag fraction of 0.5 indicates that each tree is developed using a random selection of 50 percent of the

data. The learning rate influences the total number of trees evaluated for a model, while tree complexity controls whether interactions are fitted, with a value of 3 allowing the assessment of up to 3-way interactions. Variable relative importance (VRI) was calculated using formulae developed by Friedman (2001) and implemented in the R *gbm* library to estimate the relative importance of predictor variables (Waite and others 2012). Calculations of VRI are based on the number of times a variable is selected for splitting, weighted by the squared improvement to the models as a result of each split, averaged over all trees. The relative importance of each variable is scaled so that the sum adds to 100, with higher numbers indicating stronger influence on the modeled response. Due to the size of the training dataset, we implemented a k-fold cross-validation technique using the R function *gbm.step*. The k-fold cross-validation splits the dataset into *k* partitions, keeping one partition for testing and the remaining partitions for fitting the model (Hastie and others 2009). This technique generally has low bias, and the predictive performance of a k-fold cross-validation and validation using an independent dataset is highly similar (Elith and others 2008). Additionally, k-fold cross-validation is known to provide a computational advantage over leave-one-out techniques and provides a more accurate estimate of the test error rate (James and others 2013). Goodness of fit was measured using the equivalent R^2 , estimated as:

$$(TD - RD) / TD$$

where

TD = total deviance

RD = residual deviance

Initially we developed an eight-variable BRT model using the primary subset of ERFMs outlined above. Boosted regression tree approaches have been shown to overfit models (Aertsen and others 2010, Elith and others 2008). Therefore, we developed a reduced-variable model using only those variables identified as having a relative importance >10 percent (fig. 5.3). The final model variables were selected after evaluating a Spearman rank correlation matrix of explanatory variables (table 5.2) and the effects on model fit (i.e., equivalent R^2), and by examining the PDPs of all eight explanatory variables (not shown). This secondary evaluation allowed us to reduce the number of explanatory variables from eight to four without a loss of variability accounted for by the BRT response model. The final reduced four-variable model identified those variables most critical for assessing the effects of climate, streamflow, and land use changes on FSR and insured a high level of parsimony for use in future management scenarios. We used the final reduced

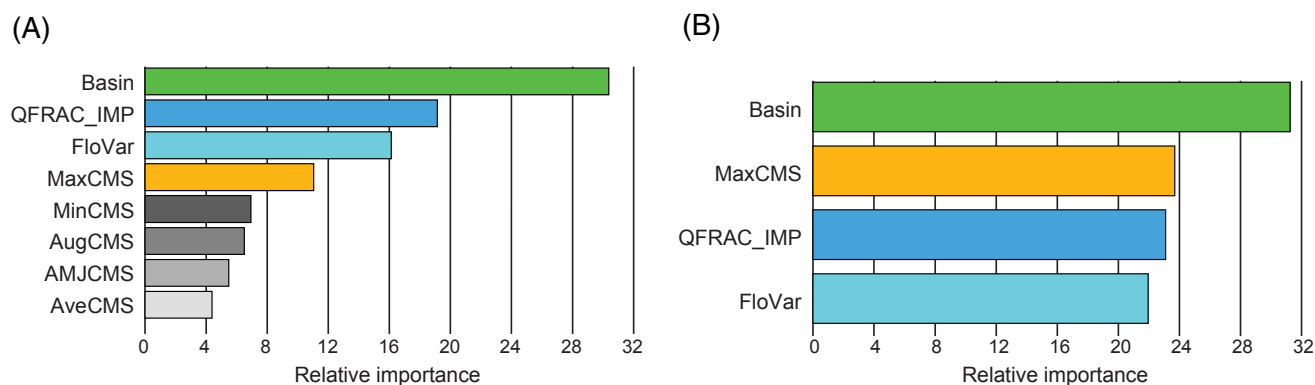


Figure 5.3—Summary of the relative importance of the predictor variables included in (A) the full eight-variable (equivalent $R^2 = 0.47$) and (B) four-variable (equivalent $R^2 = 0.50$) boosted regression tree models. [MinCMS = minimum monthly streamflow in $\text{m}^3 \text{s}^{-1}$; MaxCMS = maximum monthly streamflow; AveCMS = average monthly streamflow; AMJCMS = average streamflow for April, May, and June (spring flow); AugCMS = average streamflow for August (summer flow); FloVar = measure of the coefficient of monthly streamflow variability; QFRAC_IMP = proportion of surface flow coming from impervious surfaces; Basin = the specific river basin in which the training site is located.]

Table 5.2—Spearman correlations and p -values (in parentheses)^a of predictor variables for the boosted regression tree (BRT) models across the 385 North Carolina Division of Water Resources (NCDWR) sample sites

Variable	Basin	AveCMS	MinCMS	MaxCMS	AMJCMS	AugCMS	FloVar	QFRAC_IMP	FSR
Basin		0.07 (0.1802)	0.01 (0.8556)	0.11 (0.0258)	0.04 (0.4061)	0.02 (0.6536)	0.11 (0.0310)	-0.15 (0.0025)	0.1 (0.0508)
AveCMS			0.96 (<0.0001)	0.99 (<0.0001)	0.99 (<0.0001)	0.94 (<0.0001)	-0.22 (<0.0001)	0.05 (0.2893)	0.2 (<0.0001)
MinCMS				0.9 (<0.0001)	0.96 (<0.0001)	0.99 (<0.0001)	-0.42 (<0.0001)	0.11 (0.0359)	0.13 (0.0092)
MaxCMS					0.96 (<0.0001)	0.88 (<0.0001)	-0.09 (0.0869)	0.01 (0.8612)	0.22 (<0.0001)
AMJCMS						0.94 (<0.0001)	-0.29 (<0.0001)	0.03 (0.6049)	0.18 (0.0004)
AugCMS							-0.42 (<0.0001)	0.13 (0.0128)	0.12 (0.0147)
FloVar								-0.21 (<0.0001)	0.2 (<0.0001)
QFRAC_IMP									-0.21 (<0.0001)
FSR									

^a Bolded p -values are significant ($\alpha < 0.05$). Bolded variables represent those retained in the four-variable BRT model.

AveCMS = average monthly streamflow; MinCMS = minimum monthly streamflow; MaxCMS = maximum monthly streamflow; AMJCMS = average streamflow for April, May, and June (spring flow); AugCMS = average streamflow for August (summer flow); FloVar = measure of the coefficient of monthly streamflow variability; QFRAC_IMP = proportion of surface flow coming from impervious surfaces; FSR = fish species richness; QFRAC_IMP = the proportion of surface flow coming from impervious surfaces.

four-variable BRT model to predict FSR for all 385 NCDWR sample sites and regressed observed FSR against predicted FSR with a 95-percent confidence interval (Piñeiro and others 2008).

Scenarios

The final reduced four-variable model developed for the training data was then used to predict FSR in each HUC-12 in the North Carolina Piedmont under current conditions as well as three future scenarios. These scenarios included (1) projected average climate for the years 2041–2060, (2) impervious cover projections for the year 2060, and (3) plausible water withdrawals from each HUC-12. For climate projections, statistically downscaled 1/8- x 1/8-degree (~12 x 12 km) 1961–2099 monthly PPT and TEMP predicted by the National Oceanic and Atmospheric Administration’s Geophysical Fluid Dynamics Laboratory coupled climate model CM2.0 for the A2 growth and emission scenario was obtained from the World Climate Research Programme Coupled Model Intercomparison Project Phase 3 (CMIP3) dataset (Meehl and others 2007). The Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) (Nakicenovic and others 2000) characterized the A2 storyline as a very heterogeneous world with continuously increasing global population and regionally oriented economic growth with relatively slow technological change. The A2 (High) SRES scenario was selected because it represents potentially the most likely emission scenario as post-2000 global carbon emissions estimates indicate that current emissions are tracking the higher of the SRES emission projections (Raupach and others 2007). The CM2.0 climate model was selected because it represents a “mid-range” scenario among the 16 climate models evaluated in CMIP3 for the United States (Treasure and others 2014). Average monthly PPT and TEMP predictions were estimated for each HUC-12 using area-weighted means. Predicted FSR for the 2041 to 2060 time period was compared to the 1991 to 2010 time period to evaluate potential climate change effects.

Impervious surface projections for the year 2060 were derived from the U.S. Environmental Protection Agency’s Integrated Climate and Land-Use Scenarios (ICLUS) project for the A2 growth and emission scenario (Bierwagen and others 2010, USEPA 2009) to match the climate change scenario. The ICLUS project develops future impervious surface scenarios that are “broadly consistent with global-scale, peer-reviewed storylines of population growth and economic development” (USEPA 2009). Projections are based on regression models that relate the 2001 NLCD impervious surface database with housing density estimates (a derivative of demographic projections), which enables forecasting likely changes under SRES growth scenarios (scenario A2 was used for

this project) (USEPA 2009). Impervious cover effects were assessed by comparing FSR under projected 2060 impervious cover to that of 2006 using the baseline climate data from 1991 to 2010.

The North Carolina Ecological Flow Science Advisory Board (NCEFSAB) recommended a “flow-by” criteria where ecological flows should be 80–90 percent of the instantaneous modeled baseline flow (NCEFSAB 2013). Consistent with this recommendation, we modeled the effect of reduced flows on FSR by systematically decreasing the amount of total streamflow predicted for each HUC-12 in the North Carolina Piedmont from 5–25 percent at 5-percent intervals (i.e., a 95- to 75-percent flow-by), thereby bracketing the range recommended by the NCEFSAB. We then used these decreased flow values as explanatory variables in our BRT prediction models. Welch’s t-tests (Welch 1947) were performed using the R function `t.test` to test for differences between mean expected values for current conditions and values predicted under future scenarios (water withdrawals, impervious surface projections, and climate change). A t-test tests the hypothesis that predictions for future and withdrawal scenarios are equal to each other. The Welch’s modification adjusts the degrees of freedom for predictions whose variances are not equal (Welch 1947). Significant ($\alpha < 0.05$) *p*-values indicate that predictions are not equal.

RESULTS

The WaSSI model reasonably captured the magnitude and variability in observed flows at the seven validation sites within the study region (fig. 5.4, table 5.1). Model performance was satisfactory or better at all sites evaluated for classical model fit statistics. Absolute bias in mean flow was satisfactory (within ± 25 percent) at two sites, good (within ± 15 percent) at three sites, and very good (within ± 10 percent) at two sites. The NSE was near-satisfactory at one site (0.50), satisfactory (> 0.50) at two sites, good (> 0.65) at two sites, and very good (> 0.75) at two sites. The mean bias in mean flow across all sites was +6.2 percent (mean absolute bias 11.5 percent), while the mean NSE was 0.68; both statistics reflected good performance overall. Similarly, bias in the MaxCMS and FloVar ERFMs used in the four-variable flow-ecology model was generally within the range of hydrologic uncertainty (within ± 30 percent). Bias for four of the seven sites was within ± 30 percent for FloVar and was within ± 30 percent at all sites for MaxCMS. Sites 2, 3, and 4 FloVar bias was not within ± 30 percent; however, site 2 was only marginally outside the range of hydrologic uncertainty at -34 percent. FloVar bias was greatest for site 4 at 73 percent. Comments on flow modification in the USGS Gages II database indicate that there are small reservoirs in the headwaters of this catchment (Falcone 2011, Falcone and others 2010), possibly supplementing flows during

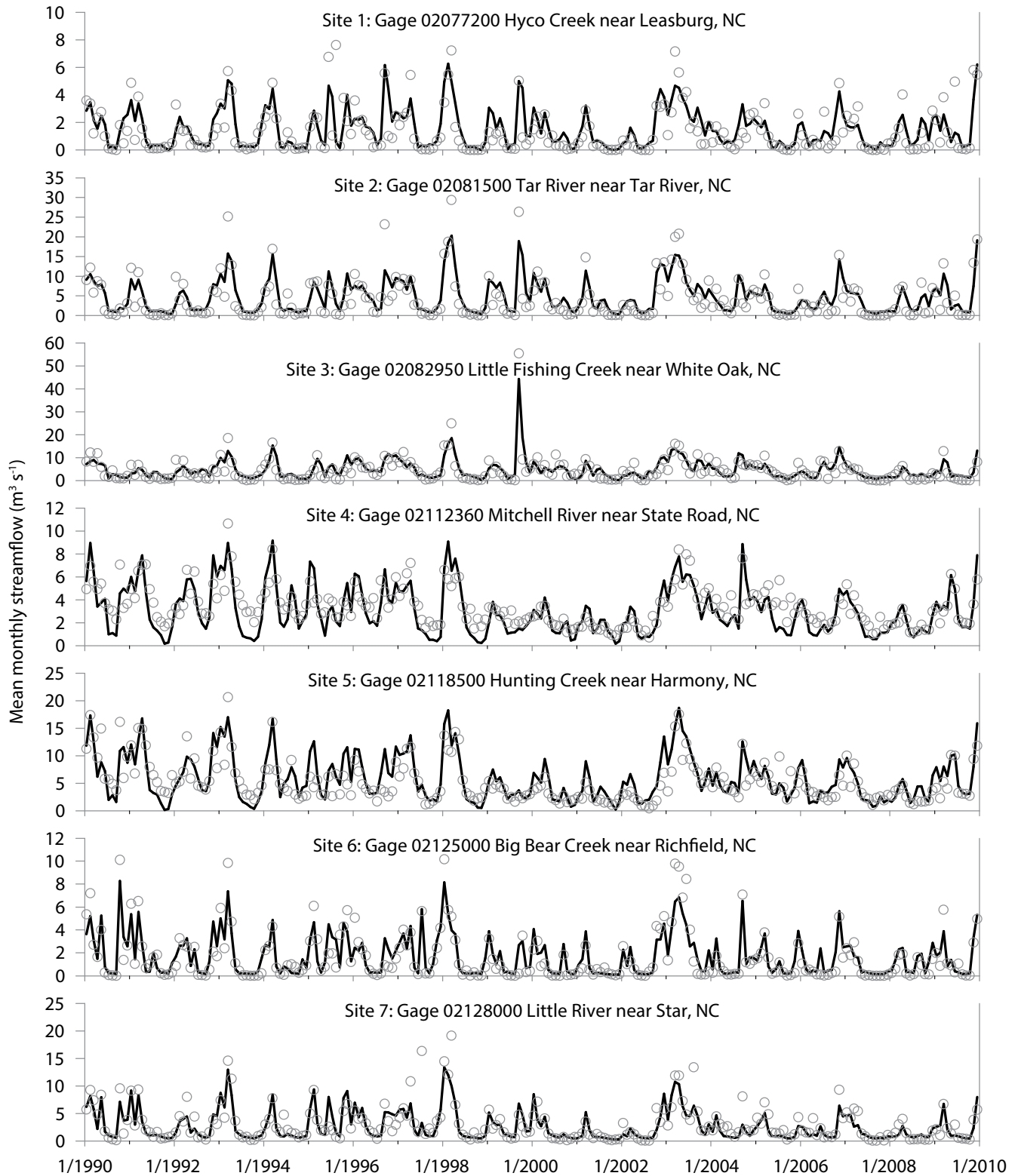


Figure 5.4—Observed (circles) and predicted (lines) mean monthly streamflow hydrographs for the seven USGS reference gauges used for WaSSI model validation.

dry periods and reducing FloVar in the observed time series relative to natural conditions simulated by WaSSI (fig. 5.4). Indeed, FloVar was lowest at site 4 among all sites, and thus small absolute differences in FloVar result in large relative differences. Overall, the validation results indicate that our hydrologic modeling approach provides reasonable approximations of ERFMs for flow-ecology modeling that fall within commonly applied bounds of uncertainty and bias.

Observed FSR values in the North Carolina Piedmont ranged from 5.0 to 28.5 across the 385 sites (fig. 5.1B, table 5.3), with an average of 16.4. Among river basins, the TAR, ROA, and NEU had the highest average FSR values, whereas the BRD, YAD, CPF, and CTB had slightly lower averages (table 5.3). By comparison, the highest MaxCMS values were found in the TAR, BRD, and NEU, while the CTB, ROA, YAD, and CPF were slightly lower (table 5.3). In addition to having the lowest MaxCMS values, the CPF had the highest QFRAC_IMP values along with the NEU, followed by the CTB, YAD, BRD, TAR, and ROA (table 5.3).

The explanatory variables in the reduced four-variable model (all variables with relative importance <10 percent removed) consisted of Basin, QFRAC_IMP, MaxCMS, and FloVar, with an estimated equivalent $R^2 = 0.50$ (table 5.4). Basin, a categorical variable, was the most influential variable in the model (31.3-percent relative importance), followed by MaxCMS (23.7 percent), QFRAC_IMP (23.1 percent), and FloVar (21.9 percent) (fig. 5.3B). All flow variables show distinct relations with the fitted values (fig. 5.5). Basin accounts for basin-specific factors such as geology, topography, habitat, and latitude, so it is not surprising that Basin had a significant influence on the model outcome. Although each variable exhibits some variability, the overall response

pattern indicates a negative response between FSR and QFRAC_IMP and a positive response between FSR and both MaxCMS and FloVar, although this response may not be linear (fig. 5.5). Further, the PDP for QFRAC_IMP shows a fairly rapid linear decline in FSR at relatively low levels of surface flow coming from impervious surfaces (fig. 5.5). Conversely, there is a strong increase in FSR between 3 and 7 $m^3 s^{-1}$ in the PDP for MaxCMS. The interactions between MaxCMS, QFRAC_IMP, and FloVar indicate that FSR is highest when MaxCMS and FloVar are high, but QFRAC_IMP is low (fig. 5.6). Across the ranges of MaxCMS and FloVar values, FSR remains quite low when QFRAC_IMP is high (fig. 5.6). The slope of the regression for observed FSR values versus those predicted by the BRT model was 0.41 (predicted FSR = $9.73 + 0.41 \times \text{observed FSR}$) with an adjusted R^2 value of 0.48, indicating a relatively good predictive fit with only slight bias across the range of values.

The northeastern part of the Piedmont including the ROA, TAR, and NEU river basins had higher FSR values than the rest of the region under the baseline scenario as illustrated in figures 5.5 and 5.7A. Projected climate change by 2041–2060 increased FSR by 0.35 species (table 5.4) on average ($p = 0.0042$), ranging from a decrease of 2.19 to an increase of 3.10 (fig. 5.7B). Projected changes in impervious cover resulted in an insignificant decrease ($p = 0.1817$) in FSR of 0.16 species across the region on average (table 5.4). Fish species richness decreased significantly across the region with increasing water withdrawals (table 5.4; figs. 5.7D and 5.8). Under the water withdrawal scenarios, a significant loss in FSR of 0.49 species was predicted with a 15-percent reduction in flow ($p = 0.0001$), while a reduction in flow of 25 percent was predicted to have an average loss of one species ($p < 0.0001$) (table 5.4).

Table 5.3—Predicted mean (standard deviation, in parentheses) ecologically relevant flow metrics (ERFMs) and fish species richness (FSR) across the 385 North Carolina Division of Water Resources sample sites for the Broad (BRD), Cape Fear (CPF), Catawba (CTB), Neuse (NEU), Roanoke (ROA), Tar-Pamlico (TAR), and Yadkin (YAD) River Basins

	BRD	CPF	CTB	NEU	ROA	TAR	YAD	All basins
FSR	15.63 (2.8)	15.48 (4.36)	13.59 (3.63)	18.95 (3.82)	19.36 (3.37)	19.91 (3.65)	15.56 (3.95)	16.35 (4.32)
MaxCMS	2.8 (3.89)	1.43 (1.68)	1.76 (1.15)	2.46 (2.06)	1.79 (1.39)	3.07 (3.68)	1.75 (1.17)	1.95 (2.05)
QFRAC_IMP	0.08 (0.07)	0.21 (0.18)	0.2 (0.17)	0.21 (0.14)	0.05 (0.04)	0.06 (0.05)	0.12 (0.12)	0.14 (0.15)
FloVar	0.75 (0.04)	0.81 (0.12)	0.74 (0.09)	0.78 (0.08)	0.8 (0.1)	0.85 (0.06)	0.83 (0.16)	0.8 (0.12)

MaxCMS = maximum monthly streamflow; QFRAC_IMP = the proportion of surface flow coming from impervious surfaces; FloVar = measure of the coefficient of monthly streamflow variability.

Table 5.4—Boosted regression tree predictions for the four-variable model across the North Carolina Piedmont ecoregion

Four-variable model (equivalent $R^2 = 0.50$)	Climate change	Impervious cover	Change in flow (water withdrawal) ^c				
	2041–2060 ^b	2041–2060 ^b	-5%	-10%	-15%	-20%	-25%
t-test p -value ^a	0.0042	0.1817	0.7909	0.1047	0.0001	<0.0001	<0.0001
Mean expected	18.04	18.04	18.04	18.04	18.04	18.04	18.04
Mean predicted	18.39	17.88	18.012	17.84	17.55	17.23	17.05
Mean change (predicted - expected)	0.35	-0.16	-0.03	-0.20	-0.49	-0.81	-0.99

^a Welch's t-tests were performed to test for differences between mean expected values for current conditions and values predicted under future scenarios (water withdrawals, impervious surface projections, and climate change). Bolded values represent a significant difference ($p < 0.05$) between current conditions and predicted values.

^b 2041–2060 represents the time period for the climate change and impervious surface scenarios.

^c Percentage values from -5 to -25 represent water withdrawal scenarios.

R^2 = coefficient of determination.

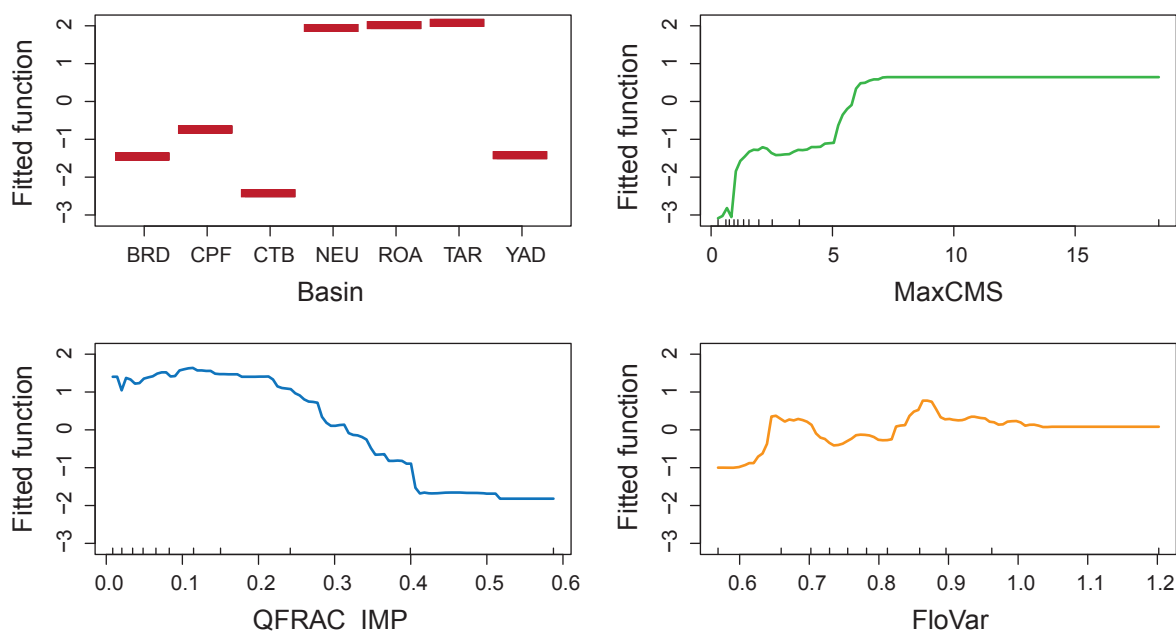


Figure 5.5—Partial dependency plots for variables in the final four-variable boosted regression tree model for FSR. Boosted regression tree partial dependency plots show the response form of FSR (y-axis = fitted function of FSR) based on the effect of individual explanatory variables with the response of all other variables removed. [FloVar = measure of the coefficient of monthly streamflow variability; MaxCMS = maximum monthly streamflow; QFRAC_IMP = the proportion of surface flow coming from impervious surfaces.]

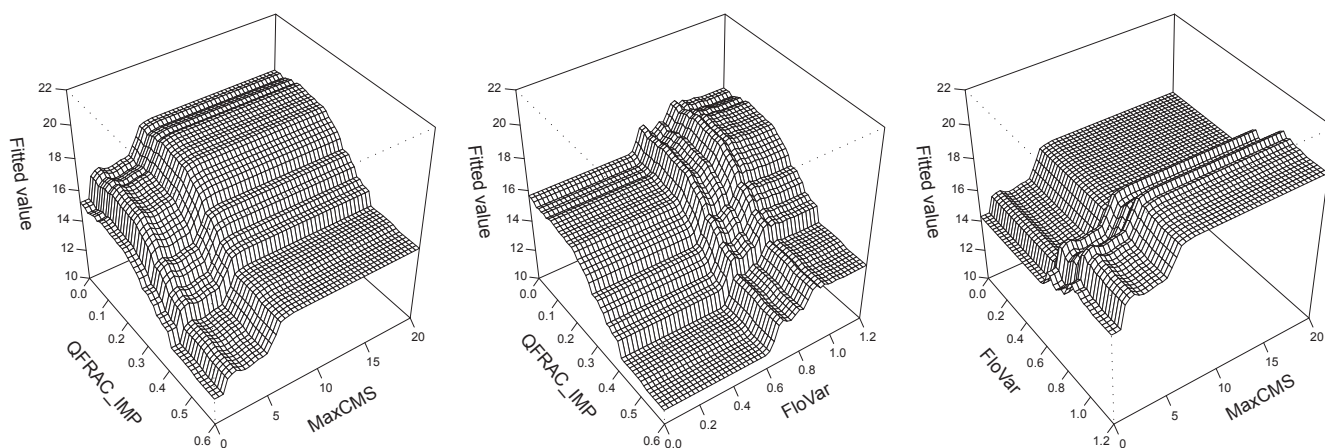


Figure 5.6—Interaction plots of QFRAC_IMP, MaxCMS, and FloVar, the three continuous variables in the four-variable model. The y-axis fitted value represents the effect of the interaction on the response variable FSR. [FloVar = measure of the coefficient of monthly streamflow variability; MaxCMS = maximum monthly streamflow; QFRAC_IMP = the proportion of surface flow coming from impervious surfaces.]

Under each future scenario, some HUC-12s were more likely to experience changes in FSR than the average HUC-12 (figs. 5.7 and 5.8). These results indicated that some HUC-12s will lose species more quickly than the region average. The hot spots shown in figure 5.8 (HUC-12s that could potentially lose more than one fish species under the 5-, 10-, 15-, and 20-percent withdrawal scenarios) identify the catchments that are most vulnerable to a loss in FSR and provide managers with a mechanism for prioritizing catchments that are most susceptible to changing water availability. The percentage of HUC-12s predicted to experience a decrease in FSR varied across river basins, with FSR in some basins (CPF, CTB, TAR, and YAD) appearing to be particularly sensitive to changes in ERFMs (table 5.5). Predicted FSR decreased in the majority of HUC-12s under all flow reduction scenarios (table 5.5). Even under the climate change scenario, where average FSR across all HUC-12s was predicted to increase, a large percentage (33 percent) of HUC-12s were predicted to decrease in FSR (table 5.5). Further, the climate change scenario showed a large increase in mean MaxCMS ($3.32\text{--}15.28\text{ m}^3\text{ s}^{-1}$) across all major river basins (table 5.6), resulting in a mean increase in FSR. MaxCMS increased in some catchments under the impervious cover scenario; however, QFRAC_IMP also increased (table 5.6) resulting in a net decrease in FSR (table 5.4).

DISCUSSION

In this study we evaluated whether relatively simple regional-scale hydrologic models can be used in conjunction with ecological data to develop empirical flow-ecology response models that predict the effect of changes in water availability on FSR at a spatial scale relevant to management. We also sought to use the

empirical flow-ecology models to identify “hot spots” of FSR change under plausible scenarios representing changes in water withdrawals (e.g., 5–25 percent), land use (derived from known build-out scenarios), and climate (the A2 high emission scenario) at the HUC-12 level. We postulated that a decline in predicted FSR would be attributable to changes in climate and increases in impervious surfaces and water withdrawals. Our findings indicate that changes in streamflow associated with plausible future water withdrawals may result in a significant loss in FSR, and for the withdrawal scenarios across the region as a whole, losses appear to be directly linked to the quantity of water withdrawn. Although the future impervious cover scenario was not found to be significant across the region as a whole, decreases in FSR of one or more species were predicted in many HUC-12s proximal to the highly urban regions of North Carolina including Charlotte, Greensboro, Raleigh-Durham, and Fayetteville (fig. 5.7C). Under the climate change scenario, FSR was actually predicted to increase significantly across all HUC-12s. While this was contrary to our hypothesis, there were many individual HUC-12s where FSR was predicted to decrease (table 5.5).

The key variable driving the average increase in FSR for the climate change scenario appears to be MaxCMS (maximum monthly streamflow for the 20-year period of record). Under this scenario, MaxCMS was the only variable from the four-variable BRT model to change substantially from the 1991–2010 average. MaxCMS was highly correlated with FSR in the training data, so these results should not be surprising. However, these findings could indicate a link between predicted changes in climate, maximum monthly or seasonal flows in river systems,

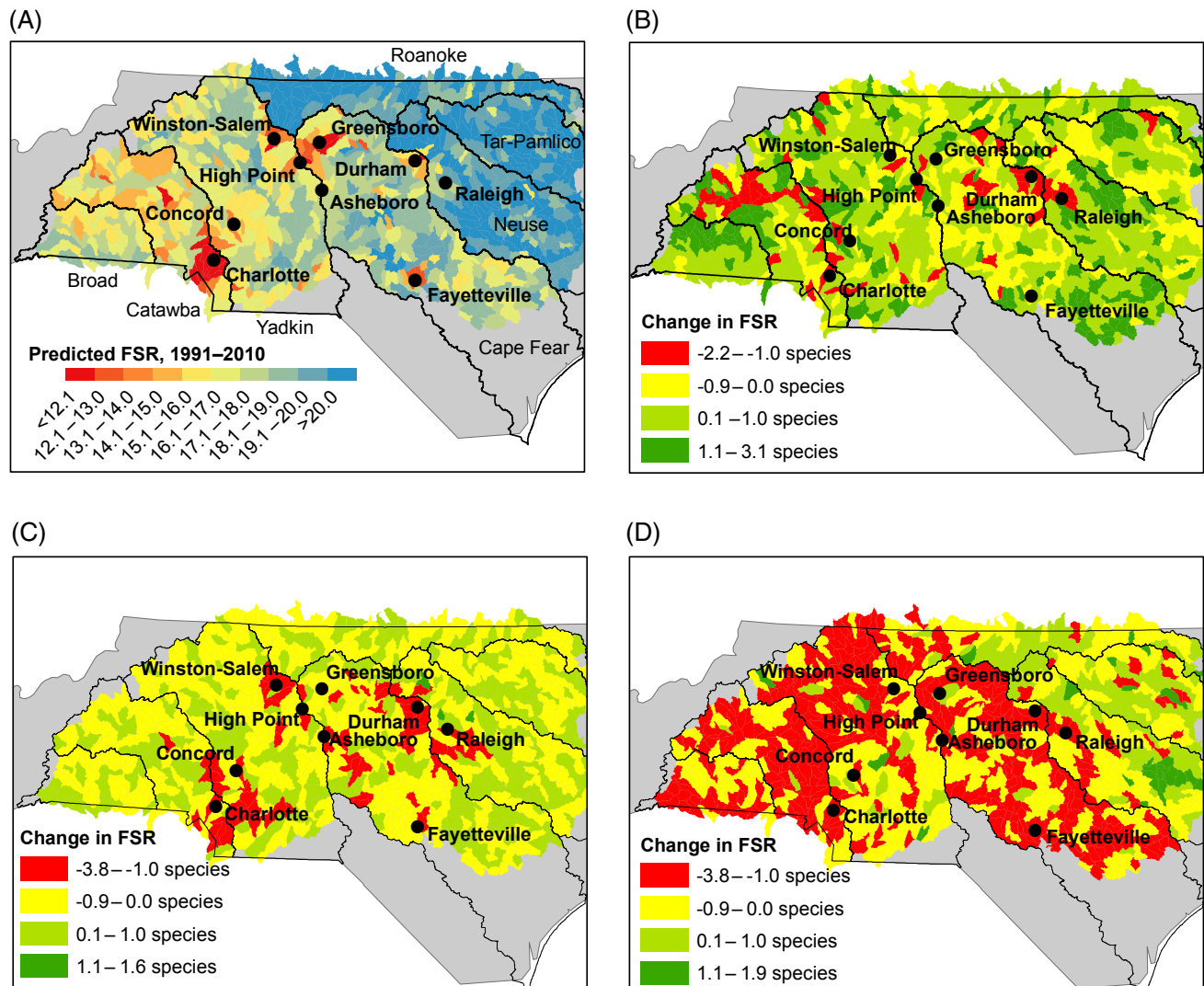


Figure 5.7—Predicted 1991–2010 baseline FSR values across the study area (A), and change in FSR under climate projections by 2060 (B), 2060 impervious projections (C), and 20-percent withdrawals (D) using the four-variable BRT model.

and increasing FSR. In contrast to the climate scenario, the flow variables for the impervious cover scenario changed very little from the 1991–2010 average over the entire study area (table 5.6), which may help explain why there were no significant changes in average FSR across all HUC-12s for that scenario. Increases in impervious surfaces are predicted to occur in and around urban areas (USEPA 2007) and likely would not impact all HUC-12s within a region the way that climate change could. For example, even though increases in MaxCMS are positively correlated with FSR, when QFRAC_IMP is high, FSR tends to be low (fig. 5.6). Conversely, when QFRAC_IMP is low, FSR tends to be high, especially in larger streams with higher MaxCMS. Some level of interaction is expected among flow attributes that summarize

information across broad spatial scales; however, such findings are essential for supporting decision makers by giving them the tools and information needed to manage water resources when faced with multiple sources of change. For example, limiting water withdrawals in an undeveloped catchment to maintain or enhance FSR may not result in the desired endpoint if land use change results in increases in impervious cover and thus increases in QFRAC_IMP. Therefore, focusing on a management action that addresses only one streamflow component or that does not take into consideration non-stationarity principles (Milly and others 2008) could cause an over-estimation of water availability and result in a significant over-allocation of the resource.

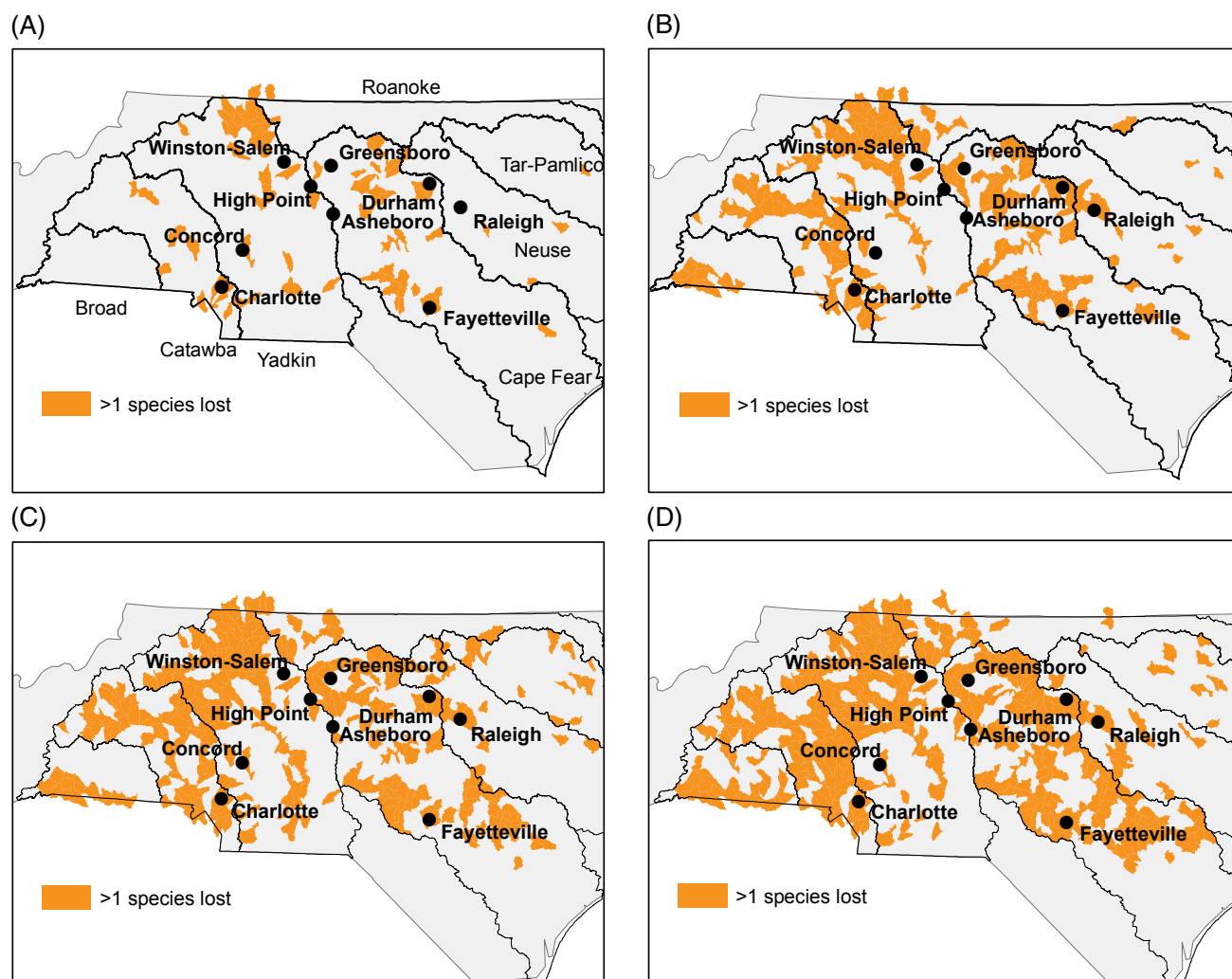


Figure 5.8—HUC-12s in the North Carolina Piedmont predicted to lose more than one fish species based on the 5-percent (A), 10-percent (B), 15-percent (C), and 20-percent (D) withdrawal scenarios.

The value of a strong hydrologic foundation cannot be understated for supporting a broader understanding of the connection between changes in water availability and sustaining the long-term viability of fish assemblages. The modeling approach presented in this paper was vital for systematically assessing regional-scale effects and identifying areas of concern (i.e., “hot spots”) where the combined effects of land cover change, climate change, and/or streamflow alteration may threaten water resources. Once hot spots are identified, fine-scale, physically based models of higher temporal resolution could potentially be applied to those areas of concern to provide more quantitative estimates of changes in water availability and support sub-monthly ERFMs using more site-specific inputs.

Response of Fish Species Richness to Hydrologic Change

Maintenance of hydrologic variability is critical to protecting biodiversity and maintaining the integrity of aquatic, riparian, and wetland ecosystems, and is the foundation of the Natural Flow Regime Paradigm (NFRP) presented by Poff and others (1997). Decades of observation of the effects of human alteration of natural flow regimes have established that streamflow variability is critical for maintaining the ecological integrity of river systems because many aquatic species have developed life-history strategies in response to these flow attributes (Hill and others 1991; Lytle and Poff 2004; Mims and Olden 2012, 2013; Poff and Ward 1989; Postel and Richter 2012; Richter and others 1997; Stalnaker 1990). The coefficient of monthly streamflow variability (FloVar) was

Table 5.5—Number (percentage, in parentheses) of 12-digit Hydrologic Unit Code (HUCs), by river basin, with a predicted decrease in fish species richness under each scenario

Basin	Number of HUCs in basin	Climate change	Impervious cover	Change in flow (water withdrawal) ^c				
		2041–2060 ^b	2041–2060 ^b	-5%	-10%	-15%	-20%	-25%
BRD	49	3 (6%)	15 (31%)	13 (27%)	13 (27%)	29 (59%)	49 (100%)	48 (98%)
CPF	215	87 (40%)	128 (60%)	148 (69%)	151 (70%)	177 (82%)	207 (96%)	211 (98%)
CTB	100	45 (45%)	50 (50%)	48 (48%)	66 (66%)	87 (87%)	98 (98%)	98 (98%)
NEU	134	39 (29%)	62 (46%)	50 (37%)	53 (40%)	54 (40%)	81 (60%)	109 (81%)
ROA	97	25 (26%)	36 (37%)	45 (46%)	31 (32%)	40 (41%)	61 (63%)	61 (63%)
TAR	85	33 (39%)	23 (27%)	57 (67%)	48 (56%)	43 (51%)	44 (52%)	59 (69%)
YAD	206	62 (30%)	95 (46%)	98 (48%)	123 (60%)	148 (72%)	189 (92%)	191 (93%)
All basins ^a	886	294 (33%)	409 (46%)	459 (52%)	485 (55%)	578 (65%)	729 (82%)	777 (88%)

^a Bolded values represent a significant difference ($p < 0.05$) between current conditions and predicted values (note that significance was tested for the region as a whole, not per basin).

^b 2041–2060 represents the time period for the climate change and impervious surface scenarios.

^c Percentage values from -5 to -25 represent water withdrawal scenarios.

BRD = Broad; CPF = Cape Fear; CTB = Catawba; NEU = Neuse; ROA = Roanoke; TAR = Tar-Pamlico; YAD = Yadkin.

Table 5.6—Average difference^a between scenarios and 2010 predictions (scenario - 2010) for changes in climate and imperviousness in major river basins across the North Carolina Piedmont

Scenario	Variable	BRD	CPF	CTB	NEU	ROA	TAR	YAD	All basins
Climate	MaxCMS	3.32	6.51	7.82	5.98	15.28	5.18	7.88	7.55
	QFRAC_IMP	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00
	FloVar	-0.07	0.00	-0.07	-0.03	-0.02	-0.09	-0.05	-0.04
Imperviousness	MaxCMS	0.01	0.24	0.21	0.51	0.04	0.03	0.18	0.21
	QFRAC_IMP	0.00	0.03	0.03	0.05	0.00	0.00	0.03	0.03
	FloVar	0.00	-0.01	-0.01	-0.02	0.00	0.00	-0.01	-0.01

^a Positive values represent a predicted increase under scenarios.

BRD = Broad; CPF = Cape Fear; CTB = Catawba; NEU = Neuse; ROA = Roanoke; TAR = Tar-Pamlico; YAD = Yadkin.

MaxCMS = maximum monthly streamflow; QFRAC_IMP = the proportion of surface flow coming from impervious surfaces; FloVar = measure of the coefficient of monthly streamflow variability.

one of the important predictors in our model. The PDP plot (fig. 5.5), before it flattens out, generally indicates a strong positive response between FSR and increasing streamflow variability which is in keeping with the principles of the NFRP. Therefore, the strength of the response for FloVar in the model underscores the importance of maintaining streamflow variability in support of a thriving fish assemblage (Bunn and Arthington 2002, Carlisle and others 2010, Poff and Zimmerman 2010).

Although the goal of restoring streamflow to its “natural” condition may be unachievable in moderately to highly degraded urban systems with high human demand for

water or in systems with numerous reservoirs designed for water-supply purposes, it still may be possible to offset future alterations in water availability resulting from climate or land use change by implementing proactive strategies that maintain variable passing flows or flow-by standards that are consistent with NFRP principles. For example, the NCEFSAB, which was tasked with developing a scientifically defensible approach to establishing flows that protect the ecological integrity of streams and rivers in North Carolina as required under Session Law 2010-143, suggested an 80–90-percent flow-by (i.e., 80–90 percent of ambient modeled flow remains in the stream; NCEFSAB 2013) in combination with a

critical low-flow component. Results of our plausible withdrawal scenarios are highly consistent with the NCEFSAB's recommendations.

Modeling Limitations

Ecologically relevant flow metrics predicted by the WaSSI model were subject to similar uncertainties associated with other hydrologic models (Caldwell and others 2015), including uncertainty in climate, land cover, soil, and LAI input data, as well as uncertainty in the representation of the physical processes that govern streamflow magnitude and timing. Unlike calibrated models, the WaSSI model will be less sensitive to errors associated with expanding the model domain to catchments not included in the model calibration process and using the model to assess the effect of climate or land cover scenarios outside of the conditions for which it was calibrated. The overall accuracy of the model was considered satisfactory given the many uncertainties in model inputs, model representation of the physical system, and observed streamflow data (see Caldwell and others 2015). We acknowledge that there is considerable uncertainty in the prediction of future climate and land cover; however, the projections we used provided a reasonable scenario of how they may change, and this was supported by our model validation results (table 5.1).

We were not able to capture some of the more specific sub-monthly streamflow attributes that may be important for fish migration and reproduction (e.g., annual daily minimum and maximum streamflow, daily streamflow exceedances and recession rates; see Kennen and others 2007, Konrad and others 2008, Olden and Poff 2003) because the WaSSI model functions at a monthly time step. However, even with this limitation, we were able to develop a significant four-variable BRT model that had good predictive power and helped to better understand the potential effects of increasing water withdrawal on FSR in the North Carolina Piedmont region. Hydrologic models vary in their levels of complexity, temporal and spatial resolution, and required level of calibration. Detailed and highly parameterized fine-resolution models such as distributed physically based watershed and rainfall-runoff models are well suited for smaller domains but can be computationally expensive and difficult to parameterize at larger scales. In contrast, easily parameterized regional-scale models such as monthly water balance models (e.g., WaSSI, the USGS Monthly Water Balance Model; Hay and McCabe 2002) are useful for assessing broad implications of streamflow alteration at a large scale and identifying potential water-limited areas but may have difficulty resolving unique sub-watershed-scale physical and ecological processes and associated anthropogenic effects. Leveraging the benefits of both large-scale models

with high-resolution models has the potential to allow more robust evaluations of the effects of water withdrawal on aquatic ecosystems. WaSSI, as demonstrated in this paper, can be used in conjunction with biological data to develop flow-ecology models that assess broad-scale regional impacts and identify specific catchments of concern ("hot spots") where the combined effects of land cover change, climate change, and/or flow alteration may threaten water resources.

There are also some limitations implicit in flow-ecology models constructed using machine learning techniques such as the BRT model presented in this paper. The strength of BRT models is that they improve on the basic averaging algorithm used in random forest (De'ath 2007); however, the improvements in prediction accuracy may come at the expense of some loss of interpretation. For example, many of the advanced machine learning techniques, such as BRT, have a tendency to overfit the data (Aertsen and others 2010). Goodness of fit measures and k-fold cross-validation techniques, as applied in this study, have been implemented to help practitioners understand and offset this limitation (Elith and others 2008). However, care should be taken to make sure results are not influenced by spatial sorting bias or spatial autocorrelation (Hijmans 2012, Randin and others 2006). A general weakness of BRT models is that they are not as familiar to scientists and managers as modeling methods such as multiple linear regression. Thus, explaining how BRT models work and how to interpret the results in a manner that supports management decisions can be a challenge. The general robustness and greater predictive power of machine learning techniques greatly outweigh their limitations and, as their application becomes more commonplace in ecology, especially for modeling non-linear relationships, their level of acceptance in the management arena will also increase.

Improvements/Future Work

The use of FSR as the primary measure of fish assemblage integrity as part of this study provides a level of simplicity and parsimony that supports scientific reproducibility and management application at the State and regional level. However, richness is only one measure of assemblage integrity, and alone it may limit broader interpretation of the hydrologic effects on fish reproduction, life-history processes, and species of special concern. Moreover, there is a need to better understand underlying mechanisms (Poff 2018) that explain local abundance and regional distributions of fish species. Examining fish species traits is one such method that has been shown to be a powerful tool in ecology for identifying trends within and among species assemblages (Statzner and others

2001) and for representing measurable characteristics based on morphological, physiological, or life-history attributes (Violle and others 2007). Additionally, there is a need to more broadly implement trait-based research in fish ecology, which to date has largely been focused on terrestrial plants and aquatic invertebrates (Verberk and others 2013). Therefore, results of this study could be enhanced through the applications of functional traits as a means to better understand the effects of hydrologic alteration on fish assemblages and support the conservation of fish species of special concern in the North Carolina Piedmont.

CONCLUSIONS

In this study, streamflow indices including the maximum monthly streamflow and the coefficient of streamflow variability were shown, in part, to be particularly important for supporting the richness of fish assemblages in the North Carolina Piedmont. The results strongly support other studies that have shown that as the magnitude of high flows and natural variability in annual streamflow

is altered, the richness of species with life-history and behavioral constraints that rely on annual high-flow patterns or fluctuations in flow for reproduction may be reduced. Implementing water management measures that meet the constraints of the NFRP has been a major challenge for management agencies. Developing practical flow-protection standards that limit groundwater and surface water withdrawals and interbasin transfers, or the implementation of designed flow releases that protect essential streamflow variability, have been difficult to achieve or have been met with strong resistance or legal actions. Therefore, it is essential that management strategies developed in collaboration with stakeholders that minimize flow alteration strive to conserve FSR. Improved water management incentives need to be established within the constraints of existing water law and government statutes that support designated uses, meet existing regulatory requirements, and promote a balance between water supply to support human needs and conservation of biological integrity.

CHAPTER 6

Synthesis

SUMMARY

Hydrologic models are commonly used to develop streamflow hydrographs for ecological flow studies because they can simulate streamflow under baseline conditions and an infinite number of scenarios of streamflow alteration. Hydrologic models vary in their levels of complexity. For example, detailed and highly parameterized fine-resolution models are well suited for smaller domains but can be computationally expensive and difficult to parameterize at larger scales. In contrast, easily parameterized large-scale models are useful for assessing broad implications of streamflow alteration at a greater spatial scale and identifying potentially water-limited areas (i.e., “hot spots”) but may have difficulty resolving unique sub-watershed-scale physical processes and associated anthropogenic effects altering streamflow. The primary objective of this study was to provide resource managers and environmental flow practitioners with some insight into the relative error in streamflow predictions among a subset of hydrologic models commonly used for water supply assessment, environmental flow studies, and climate change predictions in the Southeastern United States (SEUS) and Puerto Rico (PR). This effort was designed to evaluate, quantify, and compare the magnitude and investigate the potential causes of error associated with predicted streamflows from seven hydrologic models of varying complexity and calibration strategy. In addition, we postulated that leveraging the benefits of both large-scale models and high-resolution models will allow more robust evaluations of the effects of changes in water availability on aquatic ecosystems. Such an approach provides water managers with information necessary to better balance water resources needed to support aquatic assemblages while conserving water for long-term human uses across broad regions.

We began by creating an inventory of existing hydrologic modeling efforts in the SEUS and PR. We contacted 95 individuals from 64 unique organizations throughout the region, and 20 agreed to be interviewed. Details on their modeling efforts including the model developer, intended purpose, model framework, spatial extent, spatial and temporal resolution, time period simulated, model inputs, model outputs, and elements of environmental change represented. Validation procedure, criteria, and results were collected. Of the 64 organizations solicited,

19 represented Federal agencies, 11 represented State agencies, 32 represented universities, and 2 represented private sector organizations. The 20 individuals interviewed were developing and using hydrologic models across the SEUS and PR to answer broad questions regarding the impacts of environmental change on water resources. With the rapid pace of computing technology and growth of modeling approaches, as well as changing threats to watersheds across the landscape, it is expected that this inventory of hydrologic modeling efforts will continue to evolve, and therefore the findings presented in this report represent a snapshot of approaches and knowledge gaps in hydrologic modeling for flow-ecology science and environmental change impacts.

We then quantified and compared the magnitude and investigated the potential causes of error associated with predicting streamflows for 195 U.S. Geological Survey (USGS) continuous record gauging stations using seven hydrologic models of varying complexity and calibration strategy. Models included the Hydrological Simulation Program-Fortran (HSPF) model; the Monthly Water Balance Model (MWBm); two parameterizations of the Precipitation-Runoff Modeling System (PRMS) model; three parameterizations of the WATER model, based on TOPMODEL (a physically based, semi-distributed topographical watershed model); the Soil and Water Assessment Tool (SWAT) model; the Generalized Watershed Loading Function (GWLF)-based WaterFALL® model; and the Water Supply Stress Index (WaSSI) model. After model simulations were performed and statistical measures of model performance were computed, a model comparison workshop was convened in which 14 model developers and users representing eight different governmental, academic, and consultant organizations came together to discuss the advantages and disadvantages of different modeling approaches, sources of input data, and model calibration techniques. Findings from this study indicated that no specific hydrologic model is superior to the others evaluated for all sites and for all measures of model performance. Differences among model predictions were as likely to be related to differences in model calibration strategy as they were related to differences in model structure as increasing calibration intensity generally improved model fit. In addition, results indicated that some large-scale flow routing models

(e.g., WaSSI, MWBM) have comparable performance to the more complex, fine-scale models at a monthly time step, and large-scale models and fine-scale models have similar sensitivity to changes in precipitation and air temperature at the annual scale while sensitivity to changes in precipitation and temperature are different at the monthly scale. We do not provide recommendations for the use of any particular model that was included in this study. Instead, we stress that it is incumbent upon resource managers, environmental flow practitioners, and policymakers to consider the expertise of the modeler, the applicability of a model to a particular resource problem, the context to which the model is being applied, the timeframe being evaluated, the scale of interest, and the important components of the flow regime that may be used for model calibration to minimize error across the targeted range of flows and thus improve flow-ecology relations.

Lastly, we conducted a demonstration study for regional-scale flow-ecology response modeling for environmental change impact assessment on fish species richness (FSR) in the North Carolina Piedmont by evaluating plausible scenarios of changes in water withdrawals, climate, and impervious surfaces. Fish species richness and streamflow predictions were then used to build a boosted regression tree (BRT) flow-ecology model which was used to predict the relationship between FSR and a subset of ecologically relevant flow metrics (ERFMs) in all 12-digit Hydrological Unit Code catchments (HUC-12s) in the North Carolina Piedmont. The results of the model were then used to predict FSR under three plausible scenarios of future water withdrawals, climate change, and increases in impervious surfaces (see fig. 5.7). Finally, a “hot spot” analysis was used to identify individual HUC-12s that were most likely to be affected by changes in water availability. Using this approach, the BRT flow-ecology model was able to explain 50 percent of the variability in observed FSR using river basin, mean annual maximum monthly flow, flow variability, and the proportion of flow originating on impervious surfaces as explanatory variables. Fish species richness decreased with increasing withdrawals, and a reduction in flow of 25 percent was predicted to result in a significant average loss of one species across the region. Similarly, FSR was predicted to decrease with projected increases in impervious cover through mid-century but only in areas proximal to growing urban centers such as Charlotte, Greensboro, Raleigh-Durham, and Fayetteville. Projected climate change by mid-century increased FSR by 0.35 species on average across the region but ranged from a decrease of 2.19 species in some watersheds to an increase of 3.10 species in others. This pilot project demonstrated that the use of a large-scale hydrologic model coupled with flow-ecology models can be useful for

systematically assessing regional-scale changes in water availability and identifying areas of concern (i.e., “hot spots”) where the combined effects of land cover change, climate change, and/or streamflow alteration may threaten water resources. The study also indicates that fine-scale, physically based models of higher temporal resolution could potentially be applied to those areas of concern to provide higher resolution quantitative estimates of changes in water availability and support sub-monthly ERFMs using more site-specific inputs.

LIMITATIONS

While this report likely represents what may be the most rigorous evaluation of the use of hydrologic models for flow-ecology science compiled for the SEUS and PR, we acknowledge that it only provides an overview of the many tools and techniques available to environmental flow practitioners and water resource managers. Below we highlight some of the potential limitations of this study.

1. Only a subset of the available hydrologic models were considered in this study.
2. The models evaluated were not developed using the same calibration objective functions and input datasets, making it difficult to separate differences in model performance that may be related to the model framework (e.g., HSPF or PRMS) from differences associated with the choice of model inputs and calibration.
3. New methods are being developed all the time. The findings in this report are not stationary and should be reevaluated from time to time.
4. The capacity to fully understand non-stationary conditions associated with climate change requires rigorous calibration of models and careful attention to model inputs and representation of physical processes that may assume stationarity. For example, adjusting precipitation and other climate variables may improve model fit for historical flow observations, but these adjustments may not be appropriate when using the model to make projections using other sources of climate input (e.g., future climate change scenarios). Incorporating dynamic parameterization schemes into existing hydrologic models may provide a pathway forward for dealing with non-stationarity.
5. Models evaluated were applied to several basins in the SEUS region. The relative model performance may be different in other hydroclimatic settings (e.g., snowmelt-dominated streams and streams in arid climates).

6. There are tradeoffs between regional- and fine-scale models. Regional-scale models are often easier to parameterize but are often of a coarser resolution in space and time. Fine-scale models are often more difficult to parameterize but can have finer resolution and smaller time steps. Resource managers should consider the desired resolution of streamflow predictions when selecting a model for a particular resource problem and balance the need for that resolution with the expense in input data requirements, computational limitations, and the acceptance of a desired level of uncertainty.
7. We demonstrated that similar levels of model performance may be obtained at the monthly time step using regional- and fine-scale hydrologic models. We have also shown that regional-scale and some fine-scale hydrologic models predict similar changes in runoff for a given change in climate inputs. However, these results only provide a demonstration of the potential of multi-scale modeling approaches to evaluate environmental change effects on streamflow and ecological response. Due to differences in land cover input data, we were not able to determine whether there would be similar streamflow response to land cover change among the models evaluated. Additional study is required to determine the best way to use regional- and fine-scale models to identify hot spots or change and to develop flow-ecology relations, respectively. Models should be developed using the same inputs and calibration objective functions and then used to evaluate the same scenarios of climate and land cover change.
8. There are tradeoffs between calibrating models to best match observed high-flow or low-flow portions of the hydrograph that may affect flow-ecology modeling. Model calibration is generally intended to capture the variability and the central tendency of streamflow. It is nearly impossible to calibrate models to fit the entire range of observed streamflows because adjusting model parameters to fit a portion of the flow regime has an effect on how well the model fits observed streamflows outside of that range.
9. Many of the advanced machine learning techniques used in flow-ecology modeling, such as BRT, have a tendency to overfit the data. Goodness of fit measures and cross-validation techniques, as applied in the pilot study, have been implemented to help practitioners understand and offset this limitation. However, care should be taken to make sure results are not influenced by spatial sorting bias or spatial autocorrelation.
10. A general weakness of BRT models is that they are not as familiar to scientists and managers as modeling methods such as multiple linear regression. Thus, explaining how BRT models work and how to interpret the results in a manner that supports management decisions can be a challenge.
11. This study focused primarily on water quantity. While understanding the effects of water withdrawals on streams and other freshwater bodies in support of water availability and human consumptive use is germane to this report, the effects of changes in water quality should not be overlooked. Anthropogenic factors can be cumulative, and it is not just the quantity but also the quality of water available to ecosystems that may exacerbate conditions and affect the long-term health and vitality of aquatic systems.
12. The monthly time step of the WaSSI model may have limited our interpretation of FSR response to flow changes because we were not able to include some of the more specific sub-monthly streamflow attributes that may be important to fish migration, survival, and reproduction (e.g., August low flows or spring high flows). Further studies using daily flow attributes in combination with fish species traits (e.g., life history, habitat preference, and reproductive strategy) or other metrics that better encapsulate mechanistic response to changes in flow may improve our understanding of fish-flow relationships.

Despite these limitations, it is our hope that this report will provide environmental flow practitioners, water resource managers, and stakeholders in the SEUS with an informed pathway for developing the capacity to link streamflow and ecological response and understand some of the limitations associated with hydrologic and flow-ecology modeling efforts.

FUTURE DIRECTIONS

This study highlighted several areas that require additional research regarding the prediction of streamflow for flow-ecology science in the SEUS and PR. Our model inventory indicated that while some areas in the region were well studied (e.g., the Apalachicola-Chattahoochee-Flint Basin in Georgia, Alabama, and Florida), other areas were not (e.g., Gulf Coast States and PR). Future work should strive to build modeling capacity in these under-represented regions (see also table 2.3). In addition to incomplete spatial extent across the region, our study indicated that hydrologic models in general have difficulty in predicting extremely high and low

flows. These findings may have implications for the development of flow-ecology response models because it is often the low flows (baseflows), annual-flow pulses, and seasonality of high flows that provide the conditions necessary to support natural-assemblage complexity (Matthews 2005, Poff and Ward 1989, Poff and others 1997, Richter and others 1997, Stanford and others 1996). While improved calibration of model parameters could partially overcome limitations of modeling assumptions and simplifications of hydrologic processes, there is a clear need to understand the sources of uncertainty in prediction at the low and high end of the flow regime (e.g., potentially unrepresentative model input data including precipitation, land cover, and soil properties vs. techniques used to model specific hydrologic processes). Watersheds simulated in this model comparison study had minimal hydrologic alteration due to withdrawals, interbasin transfers, or dams so that we could assess the performance of participating models in predicting the natural flow regime. However, unaltered watersheds in the SEUS may be the exception rather than the norm. Unfortunately, comprehensive georeferenced regional databases that describe the locations and management protocols of dams, locations and volumes of withdrawals, locations and volumes of wastewater outfalls and interbasin transfers, and stormwater flow routing are incomplete or lacking, but the ongoing congressionally mandated USGS National Water Census (<https://water.usgs.gov/watercensus/>) is helping to meet this need by providing broader access to hydrologic and water budget data across the United States. Future research should continue to assemble these data using a consistent methodology so that the effects of flow alteration across regions can be assessed. In addition to flow alterations by dams and surface water withdrawals, the effects of groundwater pumping on streamflow at the regional scale is not well understood. More than 50 percent of the population in the SEUS relies on groundwater wells for drinking water (USEPA 2012), and 76 percent of all agricultural withdrawals in the SEUS originate from groundwater (Maupin and others 2014), but these groundwater withdrawals are largely unregulated and undocumented across the region. In total, groundwater withdrawals account for 25 percent of all withdrawals in the SEUS and as much as 69 percent of all withdrawals at the State level (Maupin and others 2014). Additional study will be required to better understand surface and groundwater interactions and the effects of groundwater pumping on surface water flow regimes, particularly in the Atlantic Coastal Plain where surface and shallow groundwater are more tightly coupled than other ecoregions of the SEUS.

The development of hydrographic information at ungauged locations and the aggregation of fish assemblage data for the Piedmont region of North Carolina provide two important components of the Ecological Limits of Hydrologic Alteration framework (Poff and others 2010) that can be used to support future flow-ecology modeling efforts that address non-stationarity principles (Milly and others 2008) and incorporate more temporal and quantitative elements of ecological assemblages, such as species rates. Rather than a static measure that represents a snapshot of a condition (i.e., a state) derived from a single measurement in time (such as FSR used in this study), ecological responses in a rates approach reflect temporal change (i.e., a rate) and are thus reliant on repeated measurements made over time (Wheeler and others 2018). The concept of non-stationarity presents a management challenge because the definition of natural, baseline, or reference flow conditions is dependent not only on human and natural influences on the landscape but also on our continually changing perspective of what a baseline condition represents. Hydrologic baselines are shifting and therefore reliance on restoration to a reference condition for either hydrologic or ecological systems is unsustainable. To meet this challenge, it will be important to implement ecological flows using flexible and adaptive management approaches that will support the long-term resiliency of valued ecosystems (Poff 2018). While the use of FSR as a measure of fish assemblage integrity provides a level of simplicity and parsimony that supports scientific reproducibility and management application at the State and regional level, it may limit broader interpretation of the hydrologic effects on fish reproduction, life-history processes, and species of special concern. Moreover, there is a need to better understand underlying mechanisms (Poff 2018) that explain local abundance and regional distributions of fish species. Examining fish species traits is one such method that has been shown to be a powerful tool in ecology for identifying trends within and among species assemblages and for characterizing morphological, physiological, or life-history attributes. We envision that the results of this study could be enhanced through the application of a rates approach and the inclusion of functional traits as a means to gain a better understanding of the underlying mechanistic relationship between hydrologic alteration and fish assemblage response. Such an understanding would better support the conservation of fish species of special concern in the North Carolina Piedmont and is essential to water resource management.

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List of Acronyms and Abbreviations

ACF	Apalachicola-Chattahoochee-Flint
AGWRC	Groundwater recession rate
AMJCMS	Average streamflow for April, May, and June (spring flow) in $\text{m}^3 \text{s}^{-1}$
AugCMS	Average streamflow for August (summer flow) in $\text{m}^3 \text{s}^{-1}$
AveCMS	Average monthly streamflow in $\text{m}^3 \text{s}^{-1}$
AWC	Available water capacity
BASETP	Evapotranspiration by riparian vegetation
BAU	Biological Assessment Unit
BRT	Boosted regression tree
CANMAX	Maximum canopy storage
CART	Classification and regression tree
CFS	Cubic feet per second
CFSM	Cubic feet per second per square mile
CRAM	A proprietary network flow model used to simulate water resources systems
DAYMET	Daily Meteorological Data
ELOHA	Ecological Limits of Hydrologic Alteration
ERFM	Ecologically relevant flow metrics
ET	Evapotranspiration
FloVar	Measure of the coefficient of monthly streamflow variability
FSR	Fish species richness
GCM	General Circulation Model
GIRAS	Geographic Information Retrieval and Analysis System
GIS	Geographic Information System
GR4	A lumped bucket-type daily rainfall-runoff model
GW_DELAY	Groundwater delay time
GWLF	Generalized Watershed Loading Function
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur
HRU	Hydrologic Response Unit
HSG	Hydrologic soil group
HSPF	Hydrological Simulation Program-Fortran
HUC	Hydrologic Unit Code
IDW	Inverse Distance Weighted
INFILT	Index to mean soil infiltration rate
IPCC	Intergovernmental Panel on Climate Change
LAI	Leaf area index
LCC	Landscape Conservation Cooperative
LZSN	Lower zone nominal soil moisture storage
MaxCMS	Maximum monthly streamflow in $\text{m}^3 \text{s}^{-1}$
MinCMS	Minimum monthly streamflow in $\text{m}^3 \text{s}^{-1}$
MODIS	Moderate Resolution Imaging Spectroradiometer
MWBM	Monthly Water Balance Model
NATHAT	National Hydrologic Assessment Tool
NCDWR	North Carolina Division of Water Resources

NCEFSAB	North Carolina Ecological Flows Scientific Advisory Board
NEXRAD	Next-Generation Radar
NFRP	Natural Flow Regime Paradigm
NHD	National Hydrography Dataset
NLCD	National Land Cover Database
NRCS	Natural Resources Conservation Service, U.S. Department of Agriculture
NSE	Nash-Sutcliffe Efficiency
Pbias	Monthly precipitation bias
PDP	Partial dependency plot
PEST	Parameter Estimation Tool
PET	Potential evapotranspiration
PETfac	A potential evapotranspiration correction factor
PPT	Precipitation
PRISM	Parameter-elevation Regressions on Independent Slopes Model
PRMS	Precipitation-Runoff Modeling System
QFRAC_IMP	Proportion of surface flow coming from impervious surfaces
RCoeff	Recession coefficient providing the rate of release from the saturated zone to the stream channel
RevapMN	Threshold depth of water in the shallow aquifer required for “revap” or percolation to the deep aquifer to occur
ROfac	Percentage of the total surplus water that becomes runoff
RRAWFLOW	Rainfall-Response Aquifer and Watershed Flow Model
RMSE	Root mean squared error
RTI	Research Triangle Institute
SAC-SMA	Sacramento Soil Moisture Accounting Model
SALCC	South Atlantic Landscape Conservation Cooperative
SARP	Southeast Aquatic Resources Partnership
SECO	Soil evaporation compensation factor
SCASC	Southeast Climate Adaptation Science Center, U.S. Department of the Interior
SEEP	Seepage coefficient representing infiltration losses to deep aquifer storage
SERAP	Southeast Regional Assessment Project
SEUS	Southeastern United States
Sol_AWC	Available water capacity of the soil layer
SRES	Special Report on Emissions Scenarios
SSURGO	Soil Survey Geographic database
STATSGO	State Soil Geographic database
SURLAG	Surface runoff lag coefficient
SWAT	Soil and Water Assessment Tool
TEMP	Temperature
TOPMODEL	Physically based, semi-distributed topographical watershed model
USDA	U.S. Department of Agriculture
USEPA	U.S. Environmental Protection Agency
USFS	Forest Service, U.S. Department of Agriculture
USGS	U.S. Geological Survey, U.S. Department of the Interior
WaSSI	Water Supply Stress Index model
WATER	Water Availability Tool for Environmental Resources
WATERFALL®	Watershed Flow and Allocation Modeling System
WHC	Water holding capacity

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An understanding of the applicability and utility of hydrologic models is critical to support the effective management of water resources throughout the Southeastern United States (SEUS) and Puerto Rico (PR). Hydrologic models have the capacity to provide an estimate of the quantity of available water at ungauged locations (i.e., areas of the country where a U.S. Geological Survey [USGS] continuous record gauge is not installed) and provide the baseline flow information necessary to develop the linkages between water availability and characteristics of streamflow that support ecological communities (i.e., support the development of flow-ecology response models). This report inventories and then directly examines and compares a subset of hydrologic models used to estimate streamflow at a number of gauged basins across the SEUS and PR. This effort was designed to evaluate, quantify, and compare the magnitude of error and to investigate the potential causes of error associated with predicted streamflows from seven hydrologic models of varying complexity and calibration strategy. This was accomplished by computing and then comparing classical hydrologic model fit statistics (e.g., mean bias, coefficient of determination [R^2], root mean squared error [RMSE], Nash-Sutcliffe Efficiency [NSE]) and understanding the bias in the prediction in these and a subset of ecologically relevant flow metrics (ERFMs). Additionally, streamflow predictions from a larger regional-scale hydrologic model were compared to those of several fine-scale hydrologic models under a range of hypothetical climate change scenarios to determine the range of predicted streamflow responses to fixed climate perturbations. A pilot study was conducted using predicted streamflow and boosted regression trees to develop a set of predictive flow-ecology response models to assess the potential change in fish species richness in the North Carolina Piedmont under several scenarios of water availability change. This report is intended to provide a general assessment of all the tools and techniques available to support hydrologic modeling for flow-ecology science in the SEUS and PR. It is our hope that the approach used herein to understand differences in streamflow predictions among a subset of hydrologic models that have been applied in the SEUS for developing flow-ecology response models will provide water resource managers and stakeholders with an informed pathway for developing the capacity to link streamflow and ecological response and an understanding of some of the limitations associated with these type of modeling efforts.

Keywords: Ecological flows, fish species richness, flow alteration, flow-ecology models, hydrologic models, water supply, water withdrawals.



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