To the Graduate Council:

I am submitting herewith a thesis written by Benjamin Bryan Arthur entitled "Testing the Transfer of Hydrologic Model Parameters Across Scales: Modeling the Emory River, Daddy's Creek, and Crooked Fork Watersheds." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Geography.

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TESTING THE TRANSFER OF HYDROLOGIC MODEL PARAMETERS ACROSS SCALES: MODELING THE EMORY RIVER, DADDY'S CREEK, AND CROOKED FORK WATERSHEDS

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Abstract

Modeling the hydrologic response of small watersheds is often hindered by lack of data. We cannot calibrate robust models without ample and sufficiently accurate precipitation and discharge measurements. Limited data prevent the calibration process from estimating parameter values that adequately depict the physical characteristics of the watershed. But physical characteristics change gradually over space and hydrologic processes behave in predictable ways across scales. These factors suggest that the modeling of data-limited small watersheds could be improved by using the physical characteristics of a large, data-rich watershed to estimate the characteristics of a small watershed.

This thesis presents such an application. I estimate the characteristics of the large Emory River watershed by calibrating the parameters of a VenSWM hydrologic model. VenSWM is based on the algorithms of the Stanford Watershed Model. I test how well the calibrated parameters estimate the characteristics of two subwatersheds, as determined by accuracy in predicting stream discharge in the subwatersheds, by applying them to models of the Daddy's Creek and Crooked Fork subwatersheds. I compare the adequacy of these estimates with the best possible characterization of the properties of the subwatersheds, which I obtain by calibrating hydrologic models specifically for the subwatersheds.

I find that the Emory parameters provide very accurate predictions for the Daddy's Creek watershed, which has comparable physical characteristics to the larger watershed. The Emory parameters also provide reasonably accurate predictions for the Crooked Fork watershed, which has somewhat distinct physical characteristics from the larger watershed.

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Abbreviations

BASINS	Better Assessment Science Integrating Nonpoint Sources
CWA	Clean Water Act
DEM	Digital Elevation Model
EPA	United States Environmental Protection Agency
HSPF	Hydrologic Simulation Program FORTRAN
LSPC	Loading Simulation Program C++
MRLC	Multiple Resolution Land Cover
NHD	National Hydrography Dataset
NOAA	National Oceanic and Atmospheric Administration
NPSM	Nonpoint Source Model
NRCS	Natural Resources Conservation Service
N-S	Nash-Sutcliffe R^2
PET	Potential Evapotranspiration
REA	Representative Elementary Area
SWM	Stanford Watershed Model
TDEC	Tennessee Department of Environment and Conservation
TMDL	Total Maximum Daily Load
USGS	United States Geological Survey
VenSWM	Vensim implementation of Stanford Watershed Model
WDM	Weather Data Management

Chapter 1 Introduction

Problem

Tennessee's waterways serve many functions. They supply water and hydroelectric power for residential, industrial, commercial, and agricultural uses. They support fishing, boating, and swimming. They serve as habitats for fish and other aquatic life. Water pollution hinders all of these uses. The problem is extensive, as pollution fully or partially impairs the use of almost one-third of Tennessee's stream miles (TDEC, 2000a).

Government regulations and legislation attempt to alleviate water pollution. Currently, the most prominent water quality legislation is the total maximum daily load (TMDL) program of the Clean Water Act (CWA). It requires states to develop and implement plans to make their impaired waterways meet minimum water quality standards.

Models that simulate how pollutant sources contribute to the amount of pollution in a stream facilitate the development of TMDL plans. Such models help planners choose appropriate cleanup measures by predicting how the pollutant loading in the stream will respond to alternative actions. Modeling watershed hydrology is the first step in modeling water pollution for TMDLs (Bicknell et al., 2001). Hydrologic models use precipitation and watershed characteristics to predict stream discharge. Hydrologic models of large, well-instrumented watersheds can usually be calibrated effectively.[1] In these watersheds, precipitation and stream discharge data typically span a wide variety of environmental conditions. If the calibrated model accurately simulates stream flow over this broad range of conditions, then the model parameters are likely to be good estimates of the characteristics of the watershed. This leads to confidence that the model is robust: it will accurately predict stream response to a broad range of input conditions.

[1] Calibration involves adjusting model parameters (inputs that are not altered by program computations) so that simulated discharge matches observed discharge as closely as possible (Bicknell et al., 2001). The model parameters are inputs that describe the physical characteristics of the watershed. The calibrated parameters can be considered to be estimates of the characteristics of the modeled area.

Modeling small watersheds is often infeasible because data are typically insufficient for adequate calibration. Small streams frequently do not have gages to provide complete and accurate discharge measurements. Even in streams that are gaged, the measurements frequently span only a short period of time and do not reflect a wide variety of discharge and precipitation conditions. The lack of variety prevents a thorough assessment of an estimated or conjectural parameter set. We cannot know whether the parameters will accurately predict stream response for conditions unseen in the calibration period. Short data histories may also hinder the testing of a calibrated model because data are not extensive enough both to estimate parameters and to subsequently validate them.[2]

Modeling small watersheds is further hindered by the difficulty of establishing representative precipitation. Precipitation is the most important input to watersheds and hydrologic models. Weather patterns are often localized, and stream flow depends on the precipitation that falls throughout the watershed. It is easier to establish such an average in large watersheds because they integrate precipitation over a wide area and are likely to have precipitation measurements from several locations. Models of small watersheds, on the other hand, often must rely on a single weather station (or on a few distant ones) that is unrepresentative of the weather patterns that affect that watershed.

Objectives and Hypotheses

The primary objective of my thesis is to assess the viability of using a hydrologic model of a large, well-instrumented watershed to estimate the hydrology of its data-limited subwatersheds. Effectively, this involves transferring hydrologic information from one geographic scale to another. Because hydrologic modeling is a prerequisite to pollutant modeling, such transfers would simplify TMDL modeling of small watersheds. A secondary objective is to evaluate the benefits to hydrologic modeling of combining measurements from several weather stations, instead of using a single station. This is also a question of geographic scale: is a broad-scale characterization of precipitation

[2] Validation tests the calibrated model by predicting discharge for a time period that was not used for calibration.

better than a narrow one, even if the narrow characterization uses the single weather station that provides the most complete and accurate data?

To fulfill these objectives, I transfer the parameters from a hydrologic model of the Emory River watershed (2,250 km^2) to hydrologic models of two of its subwatersheds, Daddy's Creek (390 km^2) and Crooked Fork (168 km^2). I compare the accuracy of the Emory parameters in simulating stream discharge in the subwatersheds with the accuracy of parameters estimated specifically for the subwatersheds. These three watersheds should provide a rigorous test of parameter transfer because the physical characteristics of the Daddy's Creek watershed are similar to those in the rest of the Emory watershed, while the Crooked Fork watershed has somewhat distinct physical characteristics.

At the outset, I hypothesized that the Emory parameters would yield acceptable predictions for both subwatersheds. I expected that the Emory parameters would represent the hydrology of Daddy's Creek well because the physical properties of the two watersheds are similar. I conjectured that parameters estimated specifically for Daddy's Creek would only slightly improve simulation accuracy. I expected that the Emory parameters would be less accurate for Crooked Fork because that subwatershed has somewhat distinct physical characteristics from the Emory watershed. Parameters estimated specifically for the subwatershed would be noticeably more accurate. Nevertheless, I expected the Emory parameters to provide an adequate depiction of the characteristics of the Crooked Fork watershed because major hydrologic variability usually occurs only over very large areas. For my secondary objective, I hypothesized that combining measurements from multiple weather stations would better characterize precipitation than using a single station. I based this assumption on the fact that even weather stations within a few kilometers of each other often show significant differences in precipitation during major and minor storm events. This suggested that averaging over a wider area would lead to more representative rainfall inputs.

Significance: The TMDL Program and Data Limitations

The prominence of models in the total maximum daily load (TMDL) program gives this research practical significance. The TMDL program is a significant part of the Clean Water Act, which was passed by Congress in 1972 (NRC, 2001). It requires states to clean up polluted waterways so that the waters are acceptable for selected "designated uses." Designated uses, based on how the waterway could potentially be used, have different criteria for how clean the water must be. Designated uses include fish and aquatic life protection, recreation, drinking water supply, irrigation, industrial water supply, livestock watering and wildlife, and navigation (Denton et al., 2000). In Tennessee, the Tennessee Department of Environment and Conservation (TDEC) designates the uses for every stream and lake in the state and assesses the waters for impairment or compliance. It formulates a remediation plan (called a TMDL) for each impaired water body. The United States Environmental Protection Agency (EPA) must approve each TMDL and monitor its implementation. The TMDL program is especially important today because it regulates nonpoint source pollution. Nonpoint source pollution is pollution that collects over a wide area, and includes stormwater runoff and pollutants that precipitate directly from the atmosphere. Nationally, nonpoint sources have become the principal sources of water pollution during the past ten years (NRC, 2001).

Models play an important role in the TMDL program. When writing TMDLs, the states use models to determine the sources of pollution, as well as the nature and amount of pollutants supplied by each source. Models are often the only way to obtain this information for nonpoint source pollution because these sources are hard to identify and regulate (Novotny and Chesters, 1981). Planners then calculate the amount of pollution a waterway can absorb while still meeting its designated uses. Models predict how the stream will respond to alternative pollutant reductions from various sources. As a TMDL is implemented, models can be updated with new data, which could lead to an amended TMDL (NRC, 2001).

TMDL modeling is frequently confounded by data limitations. Many waterways lack sufficient data even to allow them to be identified as impaired or compliant (NRC,

2001). When an impaired waterway can be identified, data are usually the limiting factor in modeling remediation plans (NRC, 2001). When sufficient data are unavailable to calibrate a model for a watershed, TDEC modelers estimate watershed properties using parameters developed in the model of a "similar" watershed for which more data are available. For example, the TMDL models for Fort Loudoun Lake, Crab Orchard Creek, and Roan Creek did not estimate parameters specifically for these watersheds. Instead, they used parameters from TMDL models of similar Tennessee watersheds (TDEC 2001a; TDEC, 2001b; TDEC, 2001d; TDEC, 2001e). TDEC considers watersheds to be similar if they are in the same ecoregion and have comparable drainage areas (Wang, 2002b). In many cases, however, it is impossible to find a "similar" watershed for which sufficient calibration data exist. This necessitates an expensive and time-consuming data collection campaign. To avoid this expense, states and EPA frequently implement TMDLs based on insufficient data. However, these TMDLs are often ineffective or overly expensive (NRC, 2001). The importance and cost of the TMDL program necessitate affordable and high quality analysis. Even using lowest cost cleanup methods, it may cost between $900 million and $3.2 billion to remediate all the impaired waters in the country (USEPA, 2001). Moreover, most court rulings and consent decrees require the implementation of TMDLs within the next 8 to 15 years (Lung, 2001).

My research might suggest a way to improve hydrologic and TMDL modeling of small watersheds. Most large watersheds have sufficient data to calibrate robust hydrologic models. If it is viable to transfer the calibrated parameters to data-limited subwatersheds, costly data collection campaigns can be avoided. Of local importance, Crooked Fork, one of the streams selected for this study, is listed as impaired by siltation (Denton et al., 2000). TDEC must develop a TMDL model for it, and my model results could suggest appropriate hydrologic parameters.

Organization of the Thesis

This thesis contains six chapters. This Introduction presented the problem I address, the objective, and the significance of my work. In Chapter 2, Study Area, I describe how hydrologic characteristics vary throughout my study area and the

implications for my study. In Chapter 3, Background, I put the problem in context. I introduce the model I use and explain why it is an appropriate choice. Then I review the role of scale in hydrology and show how models are used to study problems of hydrologic scale. In Chapter 4, Methods, I inventory the available data and tools, and describe how I used them. In Chapter 5, Results and Discussion, I present and analyze my results. In Chapter 6, Conclusion, I summarize my results and indicate the potential for transferring hydrologic parameters across scales.

Chapter 2 Study Area

The Emory watershed covers 2,250 km^2, primarily in Cumberland and Morgan Counties, Tennessee (see Figure 2.1).[3] The Daddy's Creek subwatershed covers 390 km^2 in the southwestern part of the Emory watershed. The Crooked Fork subwatershed is on the eastern edge, and covers 158 km^2 (see Figure 2.2). Figure 2.2 also shows the locations of the USGS gages at which I modeled discharge in each of the three streams. The drainage areas of the watersheds at each gage are 1,979 km^2 for the Emory gage, 360 km^2 for the Daddy's Creek gage, and 130 km^2 for the Crooked Fork gage (USGS, 2003a).

Water quality in Daddy's Creek meets the stream's designated uses, but Crooked Fork is impaired by siltation and habitat alteration (TDEC, 2002a). Crooked Fork will be further studied by TDEC in 2003 and its TMDL is scheduled to be formulated in 2005 (Denton et al., 2000).

Variability of Physical Characteristics

There is some spatial variability of the physical characteristics that determine hydrology throughout the Emory River watershed. The Daddy's Creek subwatershed is similar to the average characteristics of the larger watershed. The Crooked Fork subwatershed, however, shows some notable differences. The Level IV ecoregions of the Emory River watershed reflect these facts. Like most of the Emory watershed, the Daddy's Creek watershed lies primarily in ecoregion 68a, the Cumberland Plateau.[4] Daddy's Creek has a smaller drainage area than the Emory River, but otherwise TDEC would define them as "similar" because they are generally in the same ecoregion. About half of the Crooked Fork watershed is also in the Cumberland Plateau ecoregion, but the other half is in ecoregion 69d, the Cumberland Mountains. Variability of soils, land use, topography, and precipitation affects hydrologic processes in the Emory watershed.

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[3] All tables and figures are located in Appendix C.

[4] A large part of the Emory watershed also lies in ecoregion 67i, Limestone and Dolomite Valleys and Low Rolling Hills. This ecoregion does not affect my study because it lies downstream of the gage I use for discharge measurements. It therefore does not affect discharge at the gage, so my definition of the Emory watershed excludes it.

Soil properties are generally similar among the three watersheds. Loamy soils predominate. Soil types are sometimes classified into hydrologic groups A, B, C, and D. Soils in hydrologic group A have the highest permeability. Group B soils have the next highest permeability, followed by group C soils and finally by group D soils (Wanielista et al., 1997). Each of the study area watersheds includes group B and C soils. Figure 2.3 shows the extent of the various soil types and hydrologic groups in each watershed. Light colors represent soil group B and dark colors represent soil group C. The Emory watershed contains seven soil types, with group B soils covering slightly over one-third of the area above the gage (TDEC 2000a; USEPA, 2002). The prevalence of group B and C soils in the Daddy's Creek watershed is very similar to that of the Emory watershed (TDEC 2000a; USEPA, 2002). Soils in the Crooked Fork watershed have the highest average permeability, as group B soils predominate (TDEC 2000a; USEPA, 2002).

Land use is roughly comparable among the three watersheds. Figure 2.4 shows the land uses in the drainage areas above the gages for each of the three streams. The Daddy's Creek watershed has somewhat less forest and more pasture than the Crooked Fork watershed or Emory River watershed. The subwatersheds are slightly more urbanized than the larger watershed, but urbanization is only a minor factor in all three. The Emory watershed as a whole is only 1% urban, and most of this is low-intensity residential (TDEC, 2000a). Wartburg provides a small amount of urban area in the Crooked Fork watershed, but urban area only covers 2% of the watershed and 70% of the urban area is low-density residential (TDEC, 2000a). Figure 2.5 shows an area of comparatively high-density urbanization in Wartburg. Wartburg and the Brushy Mountain State Correctional Facility each have a sewage treatment plant that TDEC classifies as a "minor" discharger (TDEC, 2000a). Fairfield Glade and part of Crossville account for most of the urbanization in the Daddy's Creek watershed. The watershed is only 1.2% urban, and 57% of this is low-intensity residential (TDEC, 2000a). There are two sewage treatment plants in the subwatershed that are "minor" dischargers (TDEC, 2000a). Considering the limited urban areas, the low intensity of the urbanization that

does exist, and the lack of major point sources, urban factors are unlikely to greatly influence the hydrology of any of the three watersheds.

The difference in topography among the three watersheds is somewhat greater than differences in other factors (see Figure 2.6). The Crooked Fork watershed has greater relief, with elevations ranging between 226 and 977 m. Relief is especially high in the drainage area of the gage I use in this study. Figure 2.7 shows a view looking toward Frozen Head State Park, just upstream of the Crooked Fork gage. It illustrates the prominence of areas with high relief, but also shows some of the extensive area in the subwatershed that is relatively flat. The rest of the Emory watershed has lower relief and elevations than the Crooked Fork subwatershed. The Daddy's Creek subwatershed contains a few peaks near 800 m, but most elevations range from about 400 to 550 m. Figure 2.8 shows a representative view of topography in that subwatershed. Similar to Figure 2.7, flat areas are common. But the relief in the background is less pronounced than it is around Crooked Fork. Elevations on the Cumberland Plateau, which covers most of the Emory watershed, generally range between 350 and 600 m (TDEC, 2000a).

Variability of Precipitation

Precipitation is the most prominent source of hydrologic variability throughout the Emory River watershed. This variability is significant because precipitation is the most important model input. If precipitation is not adequately characterized, estimating model parameters will be difficult and the model will be unlikely to predict stream discharge accurately. Data from seven National Oceanic and Atmospheric Administration (NOAA) weather stations in and around the Emory watershed capture the variability (see Figure 2.9).[5]

Table 2.1 shows that there is significant precipitation variability around the watershed on an annual basis. Figure 2.10 illustrates this. The Cumberland Plateau (the western side of the watershed – Monterey and the two Crossville stations) receives more precipitation than areas east of the Plateau. For example, Knoxville usually receives

[5] Figure 2.9 also shows the Rockwood station, which I did not include in my analysis because it lacked data on many dates.

about 30 fewer cm of annual precipitation than the western stations. Lancing, located close to the center of the watershed, typically receives 15-30 fewer cm annually than the far western stations. This distribution of precipitation suggests that the Daddy's Creek watershed is slightly wetter the watershed average and that the Crooked Fork watershed is somewhat drier. There is variability even over smaller areas. The Crossville Experiment Station and the Crossville Airport are only 7 km apart but often show annual differences over 10%. Some of the variance might be attributable to differences in measurement techniques, but much of it is likely due to truly different weather conditions.

The Emory watershed shows even greater variability on time scales shorter than a year. Correlation coefficients for *daily* precipitation between pairs of weather stations from 1980-1998 are typically much less than 0.5. Some of the variability results from reporting intervals. Different stations log their daily totals at different times (e.g., a "day" at the Crossville Experiment Station runs from 6 p.m. to 6 p.m., while a "day" at the Crossville Airport runs from midnight to midnight). But truly unique weather patterns likely cause many of the differences. For example, from August 13-17, 1998, the Crossville Airport received 12.2 cm of precipitation, while the Crossville Experiment Station received only 7.3 cm. Differing measurement techniques are unlikely to explain such a large difference.

Convective and orographic storms could cause such differences. Convective storms can cause high spatial variability in rainfall, especially during the summers. They occur when the sun heats the land surface unevenly. Warm surfaces heat the air above them, causing the air to rise and cool. As the air cools, the moisture in it may condense and cause rainfall. Water bodies, urban areas, and topography that exposes hillsides to direct sunlight all contribute to uneven heating and the development of convective storms (Wanielista et al., 1997). These factors change over small areas, so convective storms are usually localized. Orographic storms are another source of localized precipitation. They occur when warm air cools as it is pushed over a hill, encouraging condensation and precipitation. High relief encourages both convective and orographic storms, so it plays a large role in the variability of rainfall. But even relatively flat areas sometimes show

considerable spatial heterogeneity in precipitation (Bradley, 1997; Bergman and Donnangelo, 2000; Englemann et al., 2002).

At the finest time resolutions, there is little correlation of precipitation among the seven weather stations. On an hourly basis, correlation coefficients between pairs of weather stations are near zero. Shifting precipitation by several hours to account for the movement of weather fronts improves the correlations by only a small amount. The low hourly correlation is important because hourly precipitation data drive the model.[6]

My study focuses on the potential for transferring parameters that describe physical properties. Noticeable physical differences among the three study area watersheds afford opportunities for testing the parameter transfer. But it will be impossible to assess the transfer without first estimating comparably accurate precipitation inputs for each of the three watersheds. The characterization of rainfall is as important as the characterization of physical properties.

Figure 2.9 showed that Lancing and the Crossville Airport are the only weather stations inside the Emory River watershed. Even if they provide the best characterization of average precipitation throughout the watershed, they cannot capture the variability shown in Table 2.1. But the other stations ring the watershed and facilitate the task of profiling that variability. Precipitation in the subwatersheds is not as well measured as in the larger watershed. Daddy's Creek and Crooked Fork do not have any weather stations inside their watershed boundaries. And the nearby stations are less likely to reflect local variability because they do not surround the subwatersheds. So, in addition to testing the effect of scale on estimating physical characteristics, I test the role of scale on precipitation profiling.

[6] The time constants that characterize rainfall infiltration and subsurface flows do create an averaging effect that mitigates the influence of some of the hourly differences. But during storm events, overland flow creates dynamics on an hourly time scale.

Chapter 3 Background

Model Used

I conducted this study using the Stanford Watershed Model (SWM). SWM was developed in the early 1960s, and was first implemented in computer code in the late 1970s (Bicknell et al., 2001). The code has progressed from the Hydrologic Simulation Program FORTRAN (HSPF) to the Nonpoint Source Model (NPSM), and recently to the Loading Simulation Program C++ (LSPC). Each of these tools is popular for total maximum daily load (TMDL) modeling (Whittemore and Beebe, 2000; Wang, 2002a).

SWM includes modules for modeling hydrology and several water pollutants. Its algorithms are based on laboratory experiments and empirical relationships from instrumented watersheds (Bicknell et al., 2001). I reproduced the most thoroughly tested version of these algorithms using the Vensim modeling environment to create VenSWM. Chapter 4 describes the creation of VenSWM and Appendix A describes its hydrology modules. When I refer to HSPF, NPSM, LSPC, or VenSWM, I am referring to the implementation of the SWM algorithms in a specific computer code.

SWM represents watershed hydrology as a system of storages and flows. Water enters the system as precipitation. It moves among interception storage, surface detention storage, upper zone storage, lower zone storage, interflow storage, and active groundwater storage. Water leaves the system through evapotranspiration, loss to deep aquifers, or stream discharge. The model uses a precipitation input and watershed characteristics including soil type, land use, evapotranspiration rates, and topography to simulate how water moves among the storages to predict the volume and timing of stream discharge. Appendix A gives a more detailed description of SWM's hydrology modules.

SWM is an appropriate tool for this study. It is a practical choice because HSPF, NPSM, and LSPC are among the most popular TMDL models. It is also practical because HSPF and NPSM have been tested and validated in a wide range of watershed sizes and physiographic settings (Laroche et al., 1996; Jacomino and Fields, 1997; Srinivasan et al., 1998; Bergman and Donnangelo, 2000; Carrubba, 2000; Englemann et al., 2002). The typical accuracy and reliability they can achieve are well established.

SWM is also a good functional choice for a study of hydrologic scale. SWM scales well because it represents a structured system of water storages and flows. This structure describes the physical processes that occur on most geographic and temporal scales in a typical watershed. SWM does not, however, attempt to replicate minute hydrologic processes appropriate at a scale of an acre or less. Its algorithms are partially empirical, and few of the relationships among the SWM processes have been tested over such small areas. The literature also suggests that SWM is a good functional choice because HSPF and NPSM parameters are sometimes successfully transferred among watersheds (Srinivasan et al., 1998; Bergman and Donnangelo, 2000).

Hydrologic Scale

The problem I study is essentially one of scale. Each model parameter represents the value of some physical characteristic averaged over the modeled area. I assess how well characteristics averaged over a large watershed, that of the Emory River, represent the hydrology of smaller areas, the Daddy's Creek and Crooked Fork subwatersheds.

In this chapter I review how hydrology operates across scales. I describe how the hydrologic response of a watershed is an aggregation of the hydrologic processes that occur on finer scales. I discuss how watershed models average the fine-scale processes to predict stream discharge, and how heterogeneity of physical characteristics, such as that found throughout the Emory River watershed, affects that averaging. I then summarize the findings of several studies that transfer model parameters among watersheds.

Hydrologic Scale Issues and How They Are Modeled

Hydrologic processes occur across a wide range of scales, spanning eight orders of magnitude spatially and temporally (Klemes, 1983). The processes include phenomena as small as rainfall infiltration on a 1 cm^2 patch of soil, and as large as weather fronts hundreds of kilometers wide. The processes are as rapid as the interception of rainwater by vegetation, and as gradual as groundwater flow. Scaling is the term for transferring information between scales (Bloschl and Sivapalan, 1995). Hydrologists often expect hydrologic processes and the models that describe them to

scale easily. But, as Klemes (1983) asked, "Can we expect a greater similarity in behavior between a 5 km^2 basin of a creek and the Orinoco Basin than between a kitchen sink and the Aswan Dam?" Extrapolating hydrologic behavior across scales requires careful attention to theory and rigorous testing of models.

The physical laws of hydrology operate in the same ways at all scales, but different processes and properties are more or less influential at different scales (Pilgrim et al., 1982; Klemes, 1983; Dooge, 1986). For example, soil characteristics such as permeability are the primary controls of hydrologic behavior of small catchments and hillslopes (Pilgrim et al., 1982; Bloschl and Sivapalan, 1995). Geologic properties such as groundwater flow and deep aquifer storage usually dominate the hydrology of large watersheds (Bloschl and Sivapalan, 1995).

Even with this varying influence, overall hydrologic behavior shows somewhat regular patterns across various scales (Dooge, 1986). Regularity emerges even if there is heterogeneity of watershed characteristics because large areas effectively "average" the hydrologic processes that occur over smaller areas (Pilgrim, 1983; Klemes, 1983). When averaging affects the natural system, it also pertains to models that represent the system. Model parameters that represent the averaged characteristics are called effective parameters. They yield the same model output as a set of parameters describing each constituent part of a region (Bloschl and Sivapalan, 1995). Integral scale, also called correlation length, describes the spatial and/or temporal area over which a process behaves uniformly and can be averaged effectively (Bloschl and Sivapalan, 1995). We can viably transfer hydrologic relationships across scales as long as we do not cross the integral scale of the processes.

A challenge of finding effective parameters is linking the observation scale with the process scale. The area or time over which we observe and measure a process is frequently different from that over which the process occurs. Scaling bridges the gap. Upscaling applies a relationship measured in a small area or for a short time period to a larger area or longer time period. One example is using the infiltration rate measured at a single plot to estimate the infiltration rate over an entire region. Another example is

extrapolating precipitation measurements from individual points to estimate the total precipitation over a region.

The upscaling concept of the representative elementary area (REA), introduced by Wood et al. (1988) has become popular in catchment modeling. The REA is a small area (usually less than 2 km^2) of a catchment whose hydrologic characteristics represent the average hydrologic properties of the larger catchment. It is a threshold area; increasing its size increases the variability of its hydrologic response and makes it a less reliable predictor of catchment hydrology. The size of the REA depends on the correlation lengths (integral scales) of topography, soils, and precipitation (Wood et al., 1988).

Besides such spatial upscaling, processes can be upscaled temporally. Temporal upscaling involves linking measurements taken over a short time period with processes measured over a longer time period. Temporal upscaling is taken for granted when TMDL modelers use hourly precipitation data to predict daily, monthly, seasonal, or annual stream discharge. The models must operate on inconsistent input and output time scales because most stream gages report discharge daily, not hourly. This data limitation reduces the power of model predictions. We cannot evaluate model performance for predicting phenomena that occur over time scales shorter than a day, including overland flow.

In contrast to upscaling, downscaling transfers a relationship measured in a large area or for a long time period to a smaller area or shorter time period (Bloschl and Sivapalan, 1995). An example of spatial downscaling is using a runoff coefficient from a large basin in a smaller basin. Downscaling often uses models to explain an observed broad-scale phenomenon by describing the local-scale processes that combine to create it. SWM is based on downscaling concepts. It simulates the volume and timing of stream discharge (an observed broad-scale process) by modeling how precipitation (another broad-scale process) is allocated among various surface and subsurface storages and flows (local-scale phenomena that cannot be directly observed).

Temporal downscaling is much less common than spatial downscaling. Indeed, it is rarely useful. For example, overland flow processes that are critical in predicting the

movement of pollutants operate on a time scale of minutes to hours. Valid hydrological algorithms over longer time scales do not exist.

This thesis is essentially a study of effective spatial parameters and integral scale at the shortest time period allowed by the data. I assess how well the effective parameters of the Emory River watershed estimate the effective parameters of the Daddy's Creek and Crooked Fork subwatersheds. Viewed another way, I test whether the subwatersheds are REAs for the larger watershed. The success of transferring parameters among the three watersheds will depend on the nature of hydrologic averaging in each watershed, and how similar the watersheds' averages are. The physical characteristics of the Emory watershed are variable but do not show abrupt spatial changes, so using a weighted average of the characteristics should be valid. For example, the model parameter representing soil permeability throughout the watershed will be a weighted average of the permeability of the seven constituent soil types. Parameters that depend on land use and topography will be weighted averages of the land use and topography throughout the watershed. The same type of averaging should apply in the subwatersheds. For example, the Daddy's Creek watershed contains three soil types with unique infiltration rates and the Crooked Fork watershed is topographically diverse, with mountainous areas and relatively flat valleys (TDEC, 2000a). My assumption is that despite these differences, a subwatershed as a whole can be characterized by spatially weighted averages.

Averaging of Hydrologic Characteristics

The averaging assumption of the last section may seem risky, but it is necessary. Some degree of averaging occurs in all hydrologic models. Variability often exists on such fine scales that it is almost impossible to create a model without significant averaging (Pilgrim et al., 1982). For example, soil characteristics often remain constant only over areas smaller than 5 km^2 (Pilgrim, 1983). In at least one case, infiltration rates varied considerably even in an 864 m^2 plot chosen specifically for its apparent homogeneity (Pilgrim et al., 1982). One study using HSPF found that refining the

modeled area below about 5.5 km^2 actually decreased simulation accuracy because it increased the influence of unmeasurable micro-scale variability (Song and James, 1992).

Modeling larger areas is often easier than modeling smaller areas because larger areas average out localized heterogeneity over areas smaller than the measurement scale. Characterizing the properties of a large area by averaging several measurements is usually more accurate than characterizing the properties of a small area using a single measurement that might be unrepresentative because it does not capture micro-scale variability. The highly variable infiltration rates mentioned above suggest that modeling a larger area would be appropriate. Also, anthropogenic factors such as impervious areas, water supply dams, and point source discharges and withdrawals can have extreme (and often difficult to measure and predict) hydrologic effects in small watersheds. Their influence decreases in larger areas (Pilgrim et al., 1982).

The difficulty of characterizing local precipitation also encourages modeling larger areas. Storms over very small areas are common in many parts of the world and a local storm can dramatically affect stream discharge in a small watershed (Woolhiser, 1996). A larger watershed will be proportionally less affected because the storm will not strike the entire drainage area. It is nearly impossible to characterize precipitation at every point in all but the smallest watersheds. It is simply too expensive to maintain a network of rain gauges dense enough to capture the local variability. Nevertheless, if several measurement locations exist throughout the watershed, it may be possible to calculate an average precipitation profile.[7] Larger watersheds are more likely to contain multiple measurement locations, enabling the creation of an average profile to remove some of the inherent uncertainty of single-station precipitation data.

Indirect Measurement

Averaging hydrologic parameters throughout a region is difficult when there is uncertainty of precipitation and/or the land has highly variable physical characteristics. In these cases we cannot simply take a weighted average of the measurements because

[7] Often, upscaling concepts are used to obtain this average by interpolating from measurement locations to estimate precipitation at other points.

we often do not know the relative areas over which the measurements apply. Finding an appropriate average is even more difficult when we cannot measure constituent values at all. For example, SWM includes parameters that represent subsurface moisture storage capacity, active groundwater storage capacity, and the fraction of water that is lost to deep aquifers. These characteristics cannot be measured in the field. We must use "indirect measurement" to determine appropriate values. We "measure" these characteristics by estimating parameters for a model that describes how a stream responds to different combinations of rainfall volume, rainfall intensity, and antecedent moisture in the watershed while effectively factoring out the influence of all of the causal variables that we *can* measure. The estimated parameters effectively "measure" the average land surface characteristics throughout the watershed. The estimated parameters can also represent the average characteristics even of parameters we can measure when micro-scale heterogeneity prevents us from determining appropriate weighted averages.

Calibrating a model using a long data history allows more accurate indirect measurement. This is especially true for models with many parameters, such as SWM, because many combinations of unmeasurable parameters can yield similar discharge simulations.[8] When the data cover a narrow range of conditions, it is difficult to know which parameter set is most appropriate. Longer data histories contain greater ranges of precipitation, antecedent moisture, and discharge conditions. Parameters that accurately simulate a variety of conditions are more likely to represent the true characteristics of the watershed. They will be more reliable for predicting stream response to conditions that did not occur during the calibration period.

Studies support the assertion that long data histories improve indirect measurement, and thus model quality. Jacomino and Fields (1997) performed four calibrations of an HSPF model of an eastern Tennessee watershed. The calibrations were distinguished by the fact that each used a unique year of precipitation and discharge data. The characteristics of the watershed did not change, so a single parameter set should have described those characteristics and adequately predicted stream response for all years.

[8] Even with 16 years of daily discharge measurements for the Emory River, I frequently found ten or more sets of reasonable parameters with statistical performances within 15% of each other.

But a single year does not contain enough precipitation variability, so the four calibrations yielded very different parameter sets. Each parameter set was noticeably less accurate in predicting discharge in the years for which it was not calibrated. On a monthly basis, the parameter sets had average absolute errors in their own years of 15.6%, 12.7%, 14.6%, and 15.3%. When applied to the three other years, the average monthly errors were 26.9%, 10.6%, 21.2%, and 16.5%, respectively. The parameter set calibrated for the fourth year was only slightly less accurate in the other years as in the year for which it was calibrated, and the parameters calibrated for the second year actually had a lower average error in the other years. But the parameter sets calibrated for the first and third years were much less accurate in the other years. These results suggest that a single parameter set can yield similar accuracy across years. It is possible that those parameters adequately estimate the characteristics of the watershed and will provide robust predictions under diverse conditions. But with only a short data history we cannot know if we have found that parameter set.

Studies of HSPF and NPSM and Their Potential for Parameter Transfer

Studies suggest that SWM is an appropriate model for studying hydrologic scale and parameter transfer. It has been applied to a range of watershed sizes. TDEC has used NPSM in TMDLs for watersheds as small as 6.36 km^2 (TDEC, 2001b), and as large as 2,774 km^2 (TDEC, 2001c). Peer-reviewed studies using HSPF and NPSM exist for catchments as small as 18 ha (Moore et al., 1988), and as large as 1,883 km^2 (Carrubba, 2000). In modeling the Emory watershed and the two subwatersheds of interest in this study, it is unnecessary to extrapolate beyond scales for which the model has been successfully applied.

Studies also show that HSPF parameters can be viably transferred among similar watersheds. This process is called regionalization (Bloschl and Sivapalan, 1995). Srinivasan et al. (1998) showed that parameter transfer is viable when watersheds have similar physical characteristics and drainage areas.[9] The HSPF hydrologic parameters they calibrated for a 23 km^2 watershed in northeastern Pennsylvania yielded similar

[9] This is comparable to TDEC's definition of similar watersheds that uses ecoregion and drainage areas.

accuracy when applied to a neighboring 39 km^2 watershed. Bergman and Donnangelo (2001) found that a single HSPF parameter set adequately characterized several southeastern Florida watersheds with drainage areas ranging from 22 km^2 to 282 km^2. They did not address scaling directly, but their results show that a single parameter set can be effective in a range of watershed sizes, as long as the physical characteristics are similar.

Differences in physical characteristics complicate parameter transfer using HSPF and NPSM, and even make difficult the estimation of average hydrologic characteristics in the calibrated watershed. Carrubba (2000) could not accurately calibrate a model of one large watershed using NPSM. She speculated that the variability of rainfall and physical characteristics (the watershed spanned two ecoregions) prevented her from finding parameters that adequately averaged conditions throughout the watershed. She concluded that accurate calibration is possible in such cases, but that the model requires more intensive calibration. Calibrated HSPF and NPSM parameters are often site-specific (Heng and Nikolaidis, 1998; Whittemore and Beebe, 2000), so physical heterogeneity is also likely to complicate parameter transfer.

None of these studies attempted to transfer parameters across spatial scales when there was some distinctness in physical characteristics across those scales. But they show that SWM can characterize the hydrologic characteristics of a large area by using parameters that represent a weighted average of the constituent areas. Before undertaking the research for this thesis, I expected to find substantial averaging (both in the natural system and in the models) of the characteristics that determine the hydrology of the Emory River watershed and its subwatersheds. I hypothesized that the nature of the averaging would allow parameters that represent the average properties of the larger watershed to adequately depict the average properties of the subwatersheds.

Chapter 4 Methods

Research Design: Comparison of Calibrations

The central objective of this research was to assess parameter transfer across scales in a hydrologic model. I did this by comparing the estimated physical characteristics of two subwatersheds, obtained through parameter transfer, with the best possible depiction of the characteristics of those subwatersheds. I first calibrated a VenSWM model of the Emory River watershed to estimate its physical characteristics. Second, I transferred the parameters from that model to models of the Daddy's Creek and Crooked Fork subwatersheds. This effectively used the estimated characteristics of the larger watershed to estimate the properties of the subwatersheds. Third, I obtained the best possible depiction of subwatershed characteristics by calibrating models specifically for the subwatersheds. Fourth, I compared the accuracy of the Emory parameters in predicting flow in each subwatershed with the accuracy of the subwatershed-specific parameters.

In this chapter I describe each of these four steps. I then explain how I created VenSWM, the tool that I used to conduct the research. Next, I review the data that I used. Finally, I describe the process I used to analyze my results.

Step 1: Calibration of the Emory River model

I created a VenSWM model of the Emory River watershed and calibrated it using different model evaluation criteria and different weather inputs. Calibration (1a) evaluated model predictions on a daily basis and used precipitation recorded at the watershed's principal weather station. Calibration (1b) also used the daily evaluation criterion, but it created a composite weather input from the precipitation measurements at six weather stations in and around the Emory River watershed. Calibration (1c) evaluated model accuracy on a seasonal basis and used composite precipitation data.

I estimated a unique set of parameter values in each of the three calibrations. Five parameters were exceptions that I set to be the same value in each calibration. The length and slope of the overland flow plane and the total watershed area are easily measurable at

many scales. We can measure them directly in most watersheds, so there is little reason to transfer them between watersheds. The calibrations also used the same annual "seasonal shape" for the lower zone evapotranspiration parameter and the interception storage parameter. That is, I estimated annual average values, but maintained a fixed relationship among the monthly values. Although this constraint could reduce prediction accuracy, I imposed it to maintain the physical reality of the parameters. Interception storage should be lower in the winters than in the summers because deciduous trees lose their leaves in the winters. Lower zone evapotranspiration should also be lower in the winters because vegetation transpires less and lower temperatures reduce evaporation.

In each of the three calibrations the model predicted mean daily discharge at the United States Geological Survey (USGS) gage at Oakdale between January 1, 1980, and December 31, 1995. To test the calibrated parameter sets, I validated them between January 1, 1996, and December 31, 1998.

Step 2: Application of the Emory River model parameters to the subwatersheds

I applied the parameters from the Emory River calibration that used the day-to-day evaluation criterion and composite weather input (calibration 1b) to a VenSWM model of each subwatershed. I changed the three parameters that represent characteristics that are directly measurable from easily accessible data (watershed area and the length and slope of the overland flow plane) to values that were appropriate for the subwatersheds. I also changed the weights placed on each weather station in the composite weather file. The new weights came from the subwatershed calibrations (calibrations 3a and 3b), instead of from the Emory calibration. We can expect that the precipitation profile in the subwatersheds is somewhat different from the average profile of the larger watershed. Using subwatershed-specific weights should therefore yield more representative precipitation. Representative precipitation is essential for evaluating parameter transfer. Unrepresentative precipitation would prevent the Emory parameters from accurately predicting discharge in the subwatersheds, even if the parameters adequately estimate the physical characteristics of the subwatersheds.

Step 3: Calibration of the subwatershed models

I calibrated a model for Daddy's Creek and a model for Crooked Fork. Both models used the daily evaluation criterion and a composite weather input. The Daddy's Creek model predicted mean daily discharge at the USGS gage near Hebbertsburg for the two-year period from October 1, 1999, to September 30, 2001. The Crooked Fork model simulated mean daily discharge at the USGS gage near Wartburg for the two-year period between October 1, 1966, and September 30, 1968.

A more robust approach to modeling the subwatersheds would have been to calibrate using one year of the data and to validate in the other year. But my intent was to compare the accuracy yielded by the Emory parameters in the subwatersheds with the best achievable accuracy. Calibrating the subwatershed models using both years provides the best possible fit with those two years. Additionally, conditions were noticeably different between the first and the second year in each subwatershed. For example, for the Crooked Fork model, Monterey received 149 cm of precipitation in the first year, but only 129 cm in the second year. With a short calibration period and a change in precipitation between years, parameters calibrated for one year are unlikely to be accurate in the other year (Jacomino and Fields, 1997). Using both years for calibration would maximize accuracy across the two years. Also, the accuracy of the discharge measurements changed between the two years for Daddy's Creek. The accuracy of discharge measurements in the first year was "fair," while that in the second year was "good" (USGS, 2000-01). Calibrating on less accurate data and validating on more accurate data would complicate the evaluation of the adequacy of the estimated parameters.

Step 4: Comparison of subwatershed prediction accuracy

The bulk of my analysis compared the accuracy of the subwatershed discharge predictions produced by the Emory parameters with the accuracy of the subwatershed predictions produced by the subwatershed-specific parameters.

Implementing the Stanford Watershed Model

I used Vensim software to reproduce the HSPF and LSPC implementations of SWM's hydrologic modules. I refer to the Vensim implementation as VenSWM.[10] Vensim is a dynamic simulation modeling environment (Ventana Systems, Inc., 1999). It has its own modeling language and a visual interface that allows the modeler to define the relationships among constants, exogenous data, and parameters. It includes tools that facilitate data analysis and presentation of results. It also includes an optimizer, which I used to calibrate the models of the three watersheds. Vensim has been used in diverse applications in business, science, and the social sciences. Schneiderman et al. (2002) recently used it to reproduce the Generalized Watershed Loading Functions model for hydrologic and water quality modeling.

I reproduced the LSPC implementation of SWM. LSPC is currently only available as a beta version and its source code is not publicly available. I therefore based VenSWM on the source code for HSPF version 12, which LSPC reproduces (Riverson, 2002). HSPF contains several alternative model components and algorithms. I determined which of these are implemented in LSPC by comparing several VenSWM simulations with analogous LSPC scenarios.

VenSWM produced slightly different simulated discharge than LSPC because of small differences in model structure. (See Appendix B for an evaluation of how closely VenSWM predictions match those of LSPC.) LSPC allows unique values to be assigned to individual land uses for several parameters. VenSWM uses a single value for those parameters, which is effectively a weighted average of the constituent land uses. HSPF does not use unique values for different land uses, so it would have been impossible to determine how LSPC implemented this new functionality without its source code. Using a single averaged value also helps focus my study on the averaging involved in modeling on these scales. (It is also likely that LSPC uses a weighted average of the values for individual land use values to make its predictions.) Another difference between LSPC and VenSWM is that VenSWM does not include a component for impervious areas.

[10] VenSWM and the data from the three watersheds I studied are archived at the University of Tennessee, Knoxville Department of Georaphy; 304 Burchfiel Geography Building; Knoxville, TN 37996.

There is little impervious area in my study area, so this had little effect on predictions. A further structural difference is that VenSWM does not explicitly represent the stream network. Instead, it approximates HSPF's first-order exponential delay mechanism for calculating the lag between when water enters the stream and when it reaches the gage. Analysis of analogous scenarios in VenSWM and LSPC showed that this approximation did not cause a noticeable difference in simulated discharge. Other differences between the models were apparent only because VenSWM and LSPC produced slightly different predictions for analogous scenarios. It is impossible to determine the exact sources of the differences without LSPC's source code. Most of them probably arise because of "programmer's art": implementations of the same model by different programmers and in different programming languages necessarily lead to slight computational differences.

Data

LSPC and VenSWM base their hydrologic simulations on an hourly weather input and topography, land use, and soil data. Their output is stream discharge at the gage location. In this section I give an overview of the required model data, how the model uses the data, and the data I used.

Weather Data

Weather is the driving input for the models, and hourly precipitation and potential evapotranspiration are required (TetraTech, Inc., 2002). Other weather parameters, such as temperature, windspeed, and solar radiation, allow simulation of optional model components that I did not use.[11]

I used two sources of weather data. One was a weather data management (WDM) file provided by the National Oceanic and Atmospheric Administration (NOAA). WDM files include data for precipitation, potential evapotranspiration, air temperature, windspeed, solar radiation, dewpoint temperature, and cloud cover. The WDM file I used was included with LSPC, and contained data from two WDM stations near the

[11] Most of these options apply only to water quality modeling and are not applicable to hydrologic simulation.

Emory watershed, Monterey and Knoxville, between January 1, 1980, and December 31, 1998. I compared its data with NOAA data I downloaded from the Internet and found that WDM data have been revised for completeness and accuracy from what are publicly available.

I downloaded data for six additional weather stations in and around the watershed from NOAA's National Climatic Data Center (NOAA, 2002). Figure 2.8 showed their locations. The downloaded data had some deficiencies that I attempted to reconcile (see below), but they provided a longer data history than the WDM file. A longer data history was necessary to cover the periods in which discharge measurements exist for the subwatersheds. Using multiple weather stations also allowed me to improve the representativeness of the precipitation input over what the two WDM stations could provide. Nevertheless, the lack of weather stations on the eastern side of the watershed makes precipitation characterization difficult. This is especially true because Lancing is the only station close to Crooked Fork, and its data do not begin until after the Crooked Fork discharge measurements end.

Discharge Data

Stream discharge is the fundamental model output. I obtained mean daily discharge data from USGS gages on each of the three streams I modeled (USGS, 2002a). Figure 2.2 showed the locations of the gages. For the Emory River model, I used the gage at Oakdale (#03540500). Mean daily discharge data for this station exist for 1927 through 2002. This is also a "real-time" gage that provides updates on the Internet every fifteen minutes. For Daddy's Creek, I used the gage near Hebbertsburg (#03539600). This is also a real-time gage. Mean daily discharge data are available from May 1, 1957, through September 30, 1968, and from October 1, 1999, through September 30, 2001. For Crooked Fork, I used the gage near Wartburg (#03539860). It recorded mean daily discharge from August 1, 1966, through September 30, 1968.

Gages estimate discharge by measuring the stage (depth) of the stream. USGS calculates discharge from the relationship between stage for a given stream and its channel geometry. USGS estimates the accuracy of these calculations. Accuracy

depends on "(1) the stability of the stage-discharge relation or, if the control is unstable, the frequency of discharge measurements; and (2) the accuracy of measurements of stage and discharge, and interpretation of records" (USGS, 2002b). Accuracy is classified as "excellent", "good", "fair", or "poor". Excellent records have 95% of the measured values within 5% of the true value, good records have 95% of the measurements within 10% of the true value, and fair records have 95% of the measurements within 15% of the true values. Measurements that do not meet these standards are "poor" (USGS, 2002b).

Emory discharge measurements are "good" for the entire period I modeled (USGS, 1980-1998). Daddy's Creek's data are "fair" in the first year, and "good" in the second year (USGS, 2000-01). Most Crooked Fork measurements in both years are "good", but they are only "fair" for flows above 500 ft^3/s before April 6, 1967 (USGS, 1967-68).

In addition to the daily data, instantaneous discharge measurements were taken at various times at locations throughout the three watersheds. These data have limited usefulness for calibrating a model because they cannot give a complete picture of hydrologic behavior. The data are temporally sparse, and thus reflect limited weather and flow conditions. The high variability of weather and stream conditions also prevents these data from being very helpful for assessing model accuracy. Even a small timing error could cause an otherwise accurate model to appear inadequate. For example, Figure 4.1 shows discharge measured at 15-minute intervals on Daddy's Creek. If a model missed the timing of the peak by just 30 minutes, there would be a very large difference between simulated and observed discharge, and the model would appear to be inaccurate. Even with many instantaneous measurements, it would be difficult to evaluate the accuracy of the model.

Other Data

I obtained data that described the physiography of the Emory River watershed from EPA's BASINS web site (www.epa.gov/ost/basins). These data were in ArcView shapefile format. They included stream network, topography, land cover, and soils.

The stream network determines how long it takes water to reach a measurement point after it enters the stream. Stream network data describe channel geometry through parameters such as the length, depth, width, and slope of the channel. The data also state the locations where the various reaches join. I did not explicitly include the stream network in VenSWM, but I used it when creating an LSPC project of the Emory River watershed. That LSPC model is what I used to verify that VenSWM is an adequate representation of SWM (see Appendix B). I used the Emory River's reach file version 1, which is produced by EPA and USGS (USEPA, 2002). This version is not as detailed as the reach file version 3 or National Hydrography Dataset (NHD), but I found that it contained fewer obvious errors. Additionally, less detailed files are often appropriate for modeling larger areas (Wang, 2002b).

Topography determines the length and slope of the overland flow plane. These factors affect how long it takes precipitation to traverse land segments and reach the stream. Topography also divides a watershed into subwatersheds. For the VenSWM model, I used a digital elevation model (DEM) from USGS to estimate the length and slope of the average overland flow plane in the three watersheds. The DEM had a horizontal resolution of 90 meters by 90 meters, and a vertical resolution of one meter (USEPA, 2002). I used topographic maps from USGS to improve the coarse resolution of the DEM. I chose several points along the streams and tributaries. To calculate the length of the overland flow plane for each of those points, I measured half the length of the slope that fed it. It is necessary to divide the length of the slope in half to describe the distance that an average raindrop falling on the slope will flow. I calculated the slope of the overland flow plane by dividing the change in elevation by those horizontal distances. I then estimated the length and slope of the overland flow plane for the entire watershed by calculating the weighted average of the lengths and slopes I had measured.

Land use affects interception storage, evapotranspiration rates, and the amount of impervious area. The BASINS data included multiple resolution land cover (MRLC) data from USGS. MRLC for the Emory River watershed uses Digital Landsat Thematic Mapper satellite imagery from 1992 (TDEC, 2000a). There are ten land cover categories in the watershed: urban, barren or mining, transitional, cropland, pasture, forest,

shrubland, grassland, water, and wetlands. EPA uses land use as the basis for its guidance about typical ranges for the parameters that represent interception storage and evapotranspiration rate (USEPA, 2000). I calculated a weighted average of these ranges based on the land uses in the three watersheds. I then widened the ranges slightly to allow for the fact that EPA's guidance uses typical values, not absolute limits on what is physically realistic. I used the expanded ranges to limit the area over which the Vensim optimizer could search during calibration (see below).

Soil type has an important effect on infiltration rate. I used STATSGO soil data from the Natural Resources Conservation Service (NRCS). STATSGO generalizes more detailed soil survey maps, and uses a resolution of 1- by 2-degree topographic quadrangle units (USEPA, 2002). Similar to land use, EPA provides guidance about typical infiltration parameter values for different soil types. I used this guidance to create ranges of expected infiltration parameter values based on the weighted average of soil types in each watershed. As with the land use data, I expanded the ranges slightly to account for the fact that realistic ranges might be somewhat wider than the ranges that are typically used. I used the expanded ranges to bound the values over which the optimizer could search during calibration.

Method of Calibrating the Models

Vensim Optimizer

HSPF, NPSM, and LSPC are usually calibrated by hand. The modeler adjusts one or a small number of parameters, and runs a simulation. He or she then compares simulated and measured discharge statistically and by visually examining graphs. He or she determines how simulated stream behavior differs from observed behavior, and adjusts appropriate parameters to make the simulation more accurate. This process continues iteratively until the best possible match is achieved. I used this procedure to calibrate an LSPC model of the Emory River. I did not use this calibration in my analysis, but it allowed me to better understand how the models are commonly used and to see how different parameters affect model output.

I used the Vensim optimizer for each VenSWM calibration. Just like calibration by hand, the optimizer iteratively adjusts parameters to achieve the "best" possible match (see below for the description of the evaluation criteria) between simulated and measured discharge. The optimizer uses a "hill-climber" algorithm that compares observed discharge with discharge simulated by a given parameter set. It uses statistical methods to determine which parameter changes are most likely to improve simulation accuracy (thus moving accuracy "uphill").

The optimizer calculates the maximum likelihood estimates for the parameters. That is, it finds the set of parameter values that maximizes the probability that the model could replicate observed discharge. The uncertainty involved in any model means that a given parameter set could yield a range of discharge predictions. But a single set of predictions is most likely, and this is what the model reports to be its predictions. The VenSWM optimizer finds the set of parameters that gives predictions as consistent as possible with the observed values. The most likely predictions from all other parameters sets are less likely to produce the observed values.

Calibration using an optimizer offers several advantages over calibrating by hand. The most important is thoroughness. The optimizer can evaluate many more parameter sets, which increases the likelihood that it will find the best possible match with the data. When calibrating the Emory River models, the optimizer evaluated millions of parameter sets. Another advantage of the optimizer is objectivity. Human judgment is not involved in calibration (with the notable exception of selecting an evaluation criterion, which is described below), so it is valid to compare the accuracy of different calibrations. A drawback of using an optimizer is that the modeler loses direct control over parameter value selection. Many modelers distrust optimizers because they may choose physically unrealistic parameters (Wang, 2002a). But the Vensim optimizer allows bounded searches, so I restricted the range of values over which the optimizer could search to physically realistic values.

Model Evaluation Criteria

I used two criteria to calibrate and evaluate the models. One criterion compared simulated and observed discharge on a daily basis and the other used seasonal and annual resolution. Both criteria are commonly used to evaluate the performance of HSPF, NPSM, and TMDL models. In Vensim, the calibration criterion is called a payoff function. It determines the distribution of model predictions around the most likely value, as described above. This effectively allows the modeler to weight the accuracy of certain predictions, for example those in a single season, more than others.

The criterion in the daily calibration was analogous to the Nash-Sutcliffe coefficient of determination (N-S or N-S R^2). I therefore used N-S to assess day-to-day simulation accuracy. N-S compares simulated discharge to the average of the measured discharge over any time span. Its formula is:

$$\text{N-S} = 1 - \frac{\Sigma\,(\text{predicted on day x} - \text{observed on day x})^2}{\Sigma\,(\text{observed on day x} - \text{average observed for modeled period})^2}$$

N-S varies between negative infinity and one. Negative values indicate that the model yields inferior predictions to simply using the average of the measured discharges (Martinec and Rango, 1989). An N-S equal to 1.0 means that the model replicates flow perfectly.

N-S can be calculated on any time basis. Monthly evaluations are often used for evaluating HSPF and NPSM, but this allows daily predictions below and above measured values to cancel out. A daily basis is probably most appropriate for my study because discharge is measured daily. Evaluation on such a fine scale is rigorous because N-S is usually much lower when evaluated over shorter time increments (Laroche et al., 1996; Srinivasan et al., 1998). Additionally, if the model were accurate on a daily basis, it would necessarily be accurate over longer time intervals.

A drawback of N-S is that it focuses on absolute errors. A high N-S could be the result of accurate simulation of high flows that masks large percentage errors in low

flows (Martinec and Rango, 1989). An additional drawback of N-S is that there is no standard for "acceptable" accuracy in the literature or in TMDL modeling.

I used the following payoff function for the calibration that used a daily basis (in ft^3/s). Numbers to the right of the "/" indicate the weight placed on that term.

Average daily streamflow / 100
Cumulative daily flow / 0.000005

The first term of the function instructs the optimizer to maximize daily N-S. The second term requires the optimizer to also consider the cumulative volume error at the end of the entire 16-year calibration period. I included the second term to account for the fact that measurements on individual days might be inaccurate, but that there should not be systematic bias over the study period. Predicted discharge should pass the reality check of having a total volume close to that of the observed total volume.

In other calibrations, I used a payoff function that considered seasonal and annual accuracy. The assessment is based on ft^3/s. As with the N-S payoff function, it uses absolute volume error instead of percentage error:

Cumulative winter flow / 100
Cumulative fall flow / 100
Cumulative summer flow / 400
Cumulative spring flow / 100
Ten percent highest flows / 0.0001
Fifty percent lowest flows / 0.0004
Final cumulative flow / 0.00005

This payoff function evaluates the total error in each season of each year and the total cumulative error over the 16-year study period. It also considers the total volume errors in highest and lowest flows for each year. TDEC uses this criterion to evaluate

Tennessee's TMDL models.[12] Unlike N-S, there is an accepted definition of a good calibration. Table 4.1 shows the targets TDEC uses (TDEC, 2000b). Each of the components is calculated in each year. Tennessee's TMDL models frequently do not achieve these targets (TDEC, 2000b; TDEC, 2002b; TDEC, 2002c).

A seasonal/annual metric is sometimes appropriate for evaluating HSPF because in many watersheds the model cannot adequately replicate flow over shorter time periods. The metric also has the advantage of revealing how well the model simulates different flow conditions. With a daily metric, accurate simulation of high flows can mask inaccurate simulation of low flows. Using a metric that specifically examines low flows and individual seasons (summers are usually dominated by low flows) helps prevent this. Evaluating different flow conditions also has practical importance in pollutant modeling. High flows usually occur after storms that wash nonpoint source pollutants off the land surface and into the stream. During low flows less water is available to dilute pollutants, which could increase pollutant concentrations over acceptability thresholds.

There are three disadvantages to using seasonal/annual calibration criteria. First, they can hide inaccuracy over shorter time scales by allowing daily overpredictions and underpredictions to cancel out. HSPF simulates on an hourly basis, so presumably it should be able to produce accurate results on time scales shorter than seasons and years. Second, the longer time base greatly reduces the data available for calibration. Instead of calibrating the Emory River model on more than 5,840 measurements (365 days per year times 16 years), the seasonal metric uses only 96 measurements (4 seasons per year times 16 years, plus 2 annual metrics per year times 16 years). Third, seasonal/annual metrics are detached from the scale of interest and control. For example, seasonal predictions of pollutant concentrations are of little use if high concentrations on individual days are enough to endanger aquatic life or human health.

Choosing a payoff function for calibrating a model requires modeler judgment. For example, the weights in my payoff functions are somewhat arbitrary. A weight of some magnitude is necessary to give each term in the function roughly similar

[12] The complete TDEC criteria also incorporate terms for yearly storm volumes and summer storm volumes.

importance. For example, in the daily payoff function above, the cumulative flow over the 16-year calibration period must be reduced to place it on generally the same scale as daily flow. But once the terms are on generally the same scale, modeler judgment determines how much weight to place on each term. Weighting cumulative flow by more than 0.000005 would give cumulative accuracy greater weight relative to daily accuracy (the payoff is based on the reciprocal of the values of its components). Some "eyeballing" of output graphs is necessary to determine the desired weighting.

Similarly, using a larger weight for summer flows than for other seasons in the seasonal payoff function required judgment. Summer should receive more weight than the other seasons because the lowest flows generally occur in the summer. Equally weighting the seasons would lead the optimizer to sacrifice large percentage (and low absolute) errors in the summer for higher absolute accuracy in other seasons. Underweighting the summer would be acceptable if simulating low flows were relatively unimportant, if data quality for low flows were poor, or if the model is missing an important hydrologic component in the summer (e.g., irrigation). It would then be valid to "miss" the summer flows to allow greater accuracy in the other seasons. I determined that this would be inappropriate because (1) simulating low flows *is* important, (2) the only gage whose accuracy depended on flow volume (Crooked Fork) suggests that measurements of *high* flows are less accurate, and (3) I do not have direct evidence of a missing model component.

Weather Inputs

I used two weather files as inputs to the models. One file used hourly precipitation data from Monterey. Monterey is the closest WDM station to each of the three studied watersheds, so TDEC would use its data for creating a TMDL model of any of the watersheds. But a single weather station may not accurately represent conditions throughout the watershed, especially when the station, like Monterey, is not even located inside the watershed boundaries.

Including multiple weather stations in HSPF and NPSM can improve simulation accuracy (Chew et al., 1991; Englemann et al., 2002). To improve the representativeness

of the weather input, I made a composite weather file that combined precipitation data measured at the six NOAA weather stations in and around the Emory River watershed (see Figure 2.8).

The composite file contained hourly data for potential evapotranspiration (PET) and precipitation. For PET, I used the data from the Monterey WDM file. This seems reasonable because PET shows little spatial variability. Indeed, the Monterey and Knoxville WDM files show a direct linear relationship between their PET, with an R^2 of 1.000 and a slope of 1.0021.[13] PET also shows little variability from year to year (e.g., PET at Monterey at 2 p.m. on October 1 is almost exactly the same year after year). Therefore, when creating PET data for the subwatershed models (whose time spans were not covered by the WDM files), I averaged the 19 years of data for that hour and date from the Monterey WDM file. The stability of PET across space and across years suggests that this approximation is adequate.

Creating composite data for precipitation is complicated because data availability varies both by station and by time period. There are several geographic interpolation methods for modeling rainfall variability between measurement points. The uneven topography of the Emory watershed, however, makes distance-based methods like inverse distance weighting or splining unattractive. Several kriging methods of interpolation are available, but these are also unlikely to provide much benefit. Kriging interpolates from point measurements using estimates of the variance around those points (Dorsel and LaBreche, 1997). Cokriging is a type of kriging that estimates the variance based on a variable that is correlated with precipitation but is better measured. In this case, that variable would be topography. But in a region with high relief, such as the Emory watershed, estimating the variance would require a very large number of measurement points, and these are not available. Cokriging also requires that the relationship between the variables is closely related (Dorsel and LaBreche, 1997), but the relationship between topography and precipitation is in fact complex. Instead, I adopted a pragmatic approach, creating an empirical model for precipitation that used daily

[13] This suggests that data for the two stations are derived from the same PET measurements.

precipitation data from six stations and hourly data from two as inputs.[14] This model built up a composite precipitation profile starting from linear combinations of pairs of daily station measurements in the following way.

1. Create a daily Crossville precipitation composite of the Airport and Experiment stations as: Airport Measurement * Airport Weight + (1 – Airport Weight) * Experiment Measurement.
2. Create a Western precipitation composite by combining Crossville and Monterey as: Monterey Measurement * West Weight + (1 – West Weight) * Crossville Composite.
3. Create a South&West precipitation composite by combining Kingston and Western as: Kingston Measurement * Kingston Weight + (1 – Kingston Weight) * Western Composite.
4. Create a Northern precipitation composite by combining Lancing and Sunbright as: Lancing Measurement * Lancing Weight + (1 – Lancing Weight) * Sunbright Measurement.
5. Create a daily Final precipitation composite by combining North with South&West: South&West Composite * North-to-West Weight + (1 – North-to-West Weight) * Northern Composite.
6. Compute the hourly distribution of precipitation for a day by adding the Monterey and Sunbright hourly measurements and dividing each hourly sum by the sum of the total precipitation for the day.[15]
7. Compute the hourly precipitation composite by multiplying the hourly fraction in Step 6 by the final daily composite in Step 5.

[14] Monterey reports hourly measurements over the entire 19 years for which stream flow measurements are available. Sunbright reports hourly measurements for about 40% of the days in the period.
[15] The hourly Monterey data in the WDM file are complete, but many dates are missing from Sunbright. When Sunbright data are missing, the model uses the Monterey data to compute the precipitation distribution over the day. Occasionally, there is an isolated hour during a day in which there is no measurement at either station. When this happens, precipitation at the Knoxville station is used.

This procedure uses all of the available measured data surrounding the watershed to determine a precipitation profile.[16] The problem is how best to weight the various measurements (Airport Weight, West Weight, Kingston Weight, North Weight and North-to-West Weight). I lack an *a priori* theory for why one measurement should be more representative than another. Therefore, I allowed the VenSWM algorithms to estimate the weather station weights at the same time they estimated the watershed hydrology parameters. This makes the composite precipitation as consistent as possible with measured stream discharge. Because there are thousands of stream flow measurements, estimating the five extra parameters does not significantly degrade confidence in the values for the hydrology parameters. (Indeed, the opposite outcome occurred.) Effectively, this approach adds a rainfall model to SWM.

[16] The description above sloughs a number of tedious details. All of the stations except Sunbright report daily totals. For Sunbright, I simply summed its hourly data to get a daily total. Data from the daily stations had to be reconciled with each other because different stations report their daily totals over different intervals and time zones. For example, Monterey reports its daily totals at 7 a.m. (i.e., a "day" at Monterey runs from 7 a.m. to 7 a.m.). The Crossville Experiment Station and Kingston report at 6 p.m., while the Crossville Airport reports at midnight. Crossville and Monterey report in Central Time, but Kingston reports in Eastern Time.

The reporting of daily precipitation over different intervals created some inaccuracy in forming the composite hourly rainfall distribution. The idea was to normalize the Monterey/Sunbright distribution to a weighted average of the daily distribution of all stations. When these stations report over different intervals, the daily averages become inconsistent. This is a source of model error. By adopting the approach described above, there is an implicit assumption that either: (a) rain always falls over the part of the day that is common to all stations, or (b) the daily offsets do not perturb the average daily totals. For the subwatershed models, which were not covered by WDM data, I used the daily totals rather than summing the hourly data. For the Emory River and Crooked Fork models, I also shifted precipitation data from stations in the Central Time Zone ahead one hour. This put them on the same basis as the discharge measurements, which are recorded at midnight Eastern Time. Also, the subwatershed models simulated outside the period covered by the complete WDM data and there were many dates missing hourly from both Monterey and Sunbright. Daily data from Monterey existed on all dates, so I approximated the unknown distributions by spreading Monterey's daily total over several hours around noon.

Another complication is that Monterey reports separate hourly and daily data, but the values often do not agree. (Different types of rain gauges measure hourly and daily data. NOAA believes that the hourly gauges under-measure moderate to severe storm events. Further, NOAA sometimes adjusts the daily readings to maximize accuracy (Hudspeth, 2003)). The hourly values from the WDM file appeared to be adjusted to maximize accuracy (i.e., summing hourly WDM data better matched the daily total than summing the hourly totals), so I added its hourly data to obtain the daily totals during the period covered by the WDM file.

Chapter 5 Results and Discussion

(1a) Emory River Calibration Using Only the Monterey Weather Station

I first calibrated a VenSWM model of the Emory River using the day-to-day evaluation criterion and weather data from Monterey only. This calibration was the "base case." I did not expect the model to accurately predict stream flow because the Monterey data would not provide a representative characterization of precipitation throughout the watershed. The Emory River watershed contains diverse precipitation patterns, and measurements from a single point are unlikely to reflect the diversity. The model turned out to be relatively accurate in predicting flows compared to the accuracy commonly achieved in the SWM literature.

Figure 5.1 shows simulated and observed daily flows at the Oakdale gage during the calibration period. The blue line shows the model predictions and the pink line shows measured discharge. The graph uses a logarithmic scale to better show the range of high and low flows. Because the y-axis scale is not linear, however, the graphs visually overstate errors in low flows and understate errors in high flows. This means that the overpredictions of the low flows are smaller than they first appear, but also that the frequent large errors in simulating high flows are especially large. Figure 5.2 zooms to the last three years of the calibration to show a more detailed view of simulation accuracy. In terms of accuracy, this period is representative of the entire 16-year calibration period. Figure 5.3 shows simulated and observed flows during the validation period. Visual examination of the three graphs shows that the calibrated model replicates observed daily flow reasonably well except for low flow conditions in the summer.

Despite the summer flows, the calibrated model is accurate in predicting daily flows when the statistical quality of the simulation is compared to earlier work. The daily Nash-Sutcliffe coefficient of determination (N-S) is 0.680 during the calibration period and falls to 0.548 during the validation period. These predictions are poor by engineering standards in some fields, but they compare favorably with what has been achieved in the HSPF and NPSM literature (see Table 5.1).

The model demonstrates mixed success in simulating flows over time intervals longer than a day. Figures 5.1, 5.2, and 5.3 show a pronounced seasonal pattern in observed stream flow. Highest flows generally occur in the winters, and lowest flows generally occur in the summers. The model generally reproduces this pattern, but it is not routinely accurate when averaged over a season. It tends to slightly underpredict the high flows in the winters and springs, and to overpredict low flows in the summers. This pattern creates the relatively high daily N-S, because N-S uses absolute daily volume error instead of fractional error. If the day-to-day evaluation criterion used to calibrate the model were based on percentage error instead of absolute error, the errors at low flow conditions would be judged to be huge. But the model was calibrated with a total volume criterion, which rewarded accurate prediction of high flows at the expense of low flows.

The statistics reinforce the seasonal nature of simulation accuracy. Table 5.2 shows mean and median seasonal errors during calibration and validation. To correspond with the metrics used to evaluate TMDL models, errors shown in the table are based on seasonal total flow, not a summary of daily errors. The errors are the fractional difference between the sum of daily observed flows over the entire season and the sum of daily simulated flows over the entire season. Table 5.2 also shows the mean and median annual errors in highest and lowest flows. As with the seasonal metrics, the highest and lowest flow metrics use total volume instead of summarizing daily errors. All of the errors in the table are based on the absolute values of the fractional error in each year to prevent overpredictions in some years from canceling out underpredictions in other years. Values that do not meet TDEC's calibration goals are in bold numerals.

Table 5.2 reinforces the message of Figures 5.1, 5.2, and 5.3 that there is a pronounced seasonal pattern in simulation inaccuracy. The model fails to meet TDEC goals for summers and low-flow periods, but it does meet them in higher-flow seasons and nearly achieves the goal for the 10% highest flows. There are two important points about the values in Table 5.2. First, they are means and medians. For each season, the predictions in some years are very accurate and the predictions in other years are very inaccurate. The observed seasonal errors are systemic, but they are not universal. Second, the criterion used to estimate these parameters used a daily basis, not these

seasonal metrics. Nevertheless, if the predictions had been accurate on a daily basis, they would have been accurate on a seasonal basis as well. But if the estimation criterion had been seasonal, day-to-day accuracy would have been sacrificed to improve seasonal results.

Table 5.2 shows that the predictions during the validation period are comparably accurate to those in the calibration period and are even superior in some cases. This result suggests that the quality of the model is not dependent on fitted data, and that the model will provide accurate predictions in other time periods. Also encouraging is that the estimated parameters meet reality checks. (Model predictions are likely to be robust in simulating future flows if the model accurately depicts the characteristics of the natural system. I constrained the model to only search over physically realistic ranges, but some of the ranges were slightly broader than what would have been *most* realistic.) Table 5.3 shows the parameter values obtained in the calibration. It also shows EPA guidance about the typical ranges used for these parameters in HSPF and NPSM modeling, as well as the "maximum expected" range (USEPA, 2000). Several parameters in this calibration have values outside the typical range, but all fall within the maximum range. I discuss parameter selection when describing the next calibration.

Figures 5.1, 5.2, and 5.3 reveal an additional statistical shortcoming of this calibration–significant autocorrelation of errors. The Durbin-Watson statistic for the entire 19-year calibration and validation period is 1.12. This poor result shows that the errors are highly correlated,[17] which suggests that either important phenomena are missing from the model or there are systematic errors in the measurements. The autocorrelation is especially prominent in the late springs and early summers, with the model consistently overpredicting the receding flows. There are model parameters (AGWRC and KVARY for groundwater flow and IRC and INTFW for interflow) that attempt to describe how flow changes over time.[18] But even after assessing millions of alternative parameter sets, the VenSWM estimation procedures were unable to find

[17] A low Durbin-Watson statistics means that if the model overpredicts on one day, it is likely to overpredict on the next day. Similarly, an underprediction on one day is likely to be followed by another underprediction. A value of 2 indicates no autocorrelation.
[18] I discuss these parameters further when discussing the results of the next calibration.

values for these parameters that would pull the predictions "back on track" without creating more significant errors.

One possible cause of the autocorrelation is that the Monterey station does not routinely record precipitation that is representative of the Emory watershed. For example, discharge peaks sharply at the end of June 1995 (see Figure 5.2), suggesting that a storm struck a significant portion of the watershed. But Monterey recorded no precipitation and the predicted discharge does not show a large change in flow. As shown by this calibration's relatively favorable N-S and several of the seasonal metrics, using a single weather station allows reasonably accurate simulations much of the time. But even a cursory visual inspection of the Monterey precipitation and observed Emory flow data shows many prominent inconsistencies. I hypothesized that a more representative weather input would greatly improve model accuracy.

(1b) Emory River Calibration Using Composite Weather and Daily Evaluation Criterion

The second calibration also used the daily evaluation of prediction accuracy. It was different from calibration (1a) because its input data combined precipitation measurements from six weather stations in and around the Emory River watershed. The VenSWM parameter estimation procedures calibrated the weight to place on each station's measurements. Using multiple weather stations to estimate model parameters greatly improves the predictions over using data only from Monterey, and prediction accuracy is much higher in this calibration than has been achieved in the literature. But despite high daily accuracy, errors still show a conspicuous seasonal pattern.

Daily Evaluation

Figure 5.4 shows simulated and observed discharge at the Oakdale gage for the 16-year calibration period. Figure 5.5 zooms to the last three years, which are representative of accuracy throughout the calibration period. As before, these graphs use a logarithmic scale. The blue line shows the simulated discharge and the pink line shows the measured discharge. Visual comparison of these graphs with Figures 5.1 and 5.2 from calibration (1a) reveals that combining data from multiple weather stations greatly

improves prediction accuracy over using data from a single station. The visual appearance is supported by the excellent daily N-S of 0.848 for this calibration, which is a substantial increase over the 0.680 from the previous calibration and is much higher than has been achieved in the HSPF and NPSM literature (see Table 5.1). Figure 5.6 shows simulated and observed discharge during the three-year validation period. Visual inspection of the graph and the very favorable daily N-S of 0.825 reveal that prediction accuracy declines very little in the validation period.[19] N-S is calculated from total volume error instead of fractional error, so the high N-S from this calibration reflects accurate prediction of high flows. Visually, the most obvious improvement in model performance between this calibration and calibration (1a) is that low flow predictions are more accurate.[20] The seasonal pattern of inaccuracy is less pronounced than in calibration (1a), but Figures 5.5 and 5.6 show that it still exists (see the Seasonal Evaluation section below).

Using multiple weather stations reduces autocorrelation of errors. The Durbin-Watson statistic for the 19-year calibration and validation period improves from 1.12 to 1.39. Figure 5.5 shows that some autocorrelation remains in the predictions. The model again does not match the rapidly receding flows from late spring into early summer. That the model achieved good day-to-day accuracy despite this autocorrelation suggests that the model structure provides a reasonable but imperfect representation of the natural processes that control seasonal flow recession. Predictions that more closely match the seasonal recession are possible by reducing several parameters, especially IRC and AGWRC. But the estimated values for these parameters are already much lower than what is commonly accepted as physically realistic in HSPF and NPSM modeling (discussed further below). Two explanations exist as to why the model could not match the seasonal recession with these parameters. One is that unique physical characteristics of the Emory River watershed justify the use of unusually low values. I have no evidence that this is the case. Another explanation is that no values for these parameters will fit the

[19] This robustness is especially encouraging because validation is commonly much less accurate than calibration (see Table 5.1).
[20] The visual improvement should not be overstated because the logarithmic scale makes even a small reduction of errors in predicting low flows appear to be large.

data because the parameters do not reflect the processes of the natural system. If this were true, it would imply that other modelers regularly have difficulty reproducing seasonal recession. This explanation is difficult to evaluate because few studies report daily data. But because the VenSWM estimation procedures evaluated millions of parameter sets without finding one that accurately reproduced the seasonal recession, we cannot dismiss this explanation.

That predictions were almost as accurate in the validation period as they were in the calibration period suggests that the model will be robust in predicting future discharge. Robustness is likely when the model parameters accurately represent the characteristics of the natural system (and the model structure allows an adequate depiction of the relevant processes in the system). Experience in HSPF and NPSM modeling supports the idea that almost all of the estimated parameters in this calibration represent the physical characteristics of the Emory River watershed. Table 5.4 shows the estimated parameter values and EPA guidance about the typical and maximum expected ranges for these parameters. For reference, the table also shows the values used in models of two nearby watersheds. White Oak Creek covers 16.1 km^2 in Anderson County, Tennessee, approximately 50 km southeast of the center of the Emory River watershed. Its HSPF model is part of EPA's HSPFParm database of reference parameter sets (Donigian et al., 1999). Sinking Creek covers 34 km^2 in Washington County, Tennessee, about 200 km east of the center of the Emory River watershed (TDEC, 2000b). The parameters are from an NPSM model that TDEC used to formulate the TMDL for that watershed.

Parameter differences among the three models in Table 5.4 seem appropriate given the physical differences between the modeled areas. Almost all of the parameters in the Emory River model are well within the typical ranges per EPA guidance. Further, the White Oak Creek and Sinking Creek models show that deviations from the typical parameter ranges are common. I focus my comments on the Emory watershed's VenSWM parameters that deviate considerably from the reference values.

The estimated AGWRC for the Emory River watershed is much lower than is typical. AGWRC represents how groundwater flow changes from one day to the next,

which is a function of complex interactions among climate, topography, soils, and land use (USEPA, 2000). The deviation from the typical range is not a major concern because the parameter does not directly reflect physical characteristics. EPA guidance says that AGWRC should be estimated from observed hydrographs and then adjusted through calibration. This implies that empirical evidence better characterizes groundwater recession than *a priori* calculations using measurable physical characteristics.[21] AGWRC is generally higher in models of highly vegetated areas than in models of grasslands or urban areas (USEPA, 2000). This implies that AGWRC should be relatively high in the largely forested Emory River watershed. But increasing AGWRC from its estimated value would magnify the model's failure to track the quickly receding flows from late spring into early summer. So the empirical evidence indicates that a low AGWRC is appropriate for this watershed. There are several explanations for the deviation from typical values. One is that land use is not the fundamental driver of AGWRC in some areas. This is a likely explanation in this case. If little of the forest in the Emory River watershed is virgin forest, these areas might have different groundwater patterns than many forested areas. Additionally, the Emory watershed does not have the deep soils that characterize many forested areas. Much of the watershed is covered by thin soils with sandstone caprock. Another explanation for the low AGWRC is that the overall Emory River parameter set does not accurately reflect the physical characteristics of the watershed. Inappropriate values for other parameters might cancel out the effect of a mistaken AGWRC and allow accurate predictions. (For example, KVARY also relates to groundwater recession, so an inappropriate value for it could cause mis-estimation of AGWRC. But KVARY should also be estimated from empirical evidence (USEPA, 2000); there are no physical features that determine its value.) This interpretation seems unlikely given the robustness of the model's predictions during the validation period. A final explanation is that unique and unmeasurable physical characteristics of the Emory watershed make a lower AGWRC appropriate. The robustness of the estimated

[21] This argument also applies to IRC, for which the estimated value is also lower than is commonly used. IRC is analogous to AGWRC and represents interflow recession. EPA guidance also recommends estimating IRC using observed hydrographs, and provides no direction about what physical features determine its value (USEPA, 2000).

parameter set in predicting flow across a wide variety of precipitation and antecedent moisture conditions makes this the most likely explanation.

After calibration, the Emory River NSUR (roughness of the overland flow plane) parameter is somewhat higher than expected, given the large amount of pasture in the Emory River watershed. But NSUR remains within values commonly used for forested areas (USEPA, 2000), and the high value is likely to simply be an artifact of the estimation procedure for two other parameters. NSUR interacts with LSUR (length of the overland flow plane) and SLSUR (slope of the overland flow plane) to determine overland flow behavior. I estimated LSUR and SLSUR from GIS data and topographic maps; the VenSWM estimation procedures did not calibrate these parameters. I used conservative estimates for LSUR and SLSUR. More liberal values would have decreased the estimated NSUR to produce the same flow predictions. So although NSUR is somewhat higher than expected, the relationship among NSUR, LSUR, and SLSUR should still accurately reflect the Emory River watershed's physical characteristics.

The estimated summertime LZETP (lower zone evapotranspiration parameter) values are somewhat higher than the typical range, given the weighted average of land use in the Emory River watershed. But the values are only slightly higher than those commonly used in forested watersheds (USEPA, 2000). Further, LZETP might be a proxy for irrigation because irrigated areas have higher evapotranspiration rates than similar but unirrigated land uses. The watershed is only 2% cropland (TDEC, 2000a) and agricultural irrigation plays a minor role in hydrology. Indeed, surface water use for irrigation and livestock watering in the Emory River watershed averaged only 0.03 m^3/s in 1990 and 0.06 m^3/s in 1995 (USGS, 2003b). But numerous golf courses in Crossville are "irrigated" by sprinkler systems. Most watering would occur in the summers, which would increase summertime evapotranspiration. A slightly higher than usual summertime LZETP would reflect this factor.[22]

Some of the most important parameters to note in Table 5.4 are the weather station weightings. The weightings look appropriate given the locations of the weather stations. Perhaps the most important of these parameters is the North-to-West weight. It

[22] This point is discussed in more detail below.

determines the influence of the northern stations (Lancing and Sunbright) relative to the western stations (Monterey and the Crossville stations). It is difficult to evaluate the estimated value (0.33) because there is nothing against which to compare it. But as I show in later sections, the North-to-West weight is higher than 0.33 in the Daddy's Creek model and lower than 0.33 in the Crooked Fork model. This is consistent with my expectations. Data from the northern stations (which also happen to be in the east) are less representative of conditions in the western subwatershed (Daddy's Creek) than they are of conditions in the overall watershed, and much less representative of conditions in the eastern watershed (Crooked Fork). The other notable weather station weighting is the very low influence given to Kingston (0.24). The low weight is reasonable because Kingston is off the Cumberland Plateau. As was shown in Table 2.1, Kingston receives noticeably less annual precipitation than the other stations and is not representative of conditions in most of the Emory River watershed. The other weather station parameters are difficult to interpret because they do not have a spatial basis. They dictate the weight of one station or set of stations vis-à-vis other stations.

In summary, the calibrated model is very accurate on a daily basis during the calibration and validation periods. The robustness likely occurred because the estimated parameters accurately reflect the physical characteristics of the watershed. Three factors facilitated parameter estimation. The most important was the long calibration period. Sixteen years provide a wide range of watershed conditions for calibrating the model, which allows greater precision of indirect measurements. This is illustrated by the parameter AGWRC. Strictly following guidelines would suggest a high value, but the extensive calibration data showed that a lower value was appropriate. The second factor that aided parameter estimation was that using multiple weather stations provided a good characterization of average precipitation throughout the watershed. The estimated parameters can reflect the true physical characteristics of the watershed because they do not have to compensate for an unrepresentative input. The third factor was the use of the optimizer. It allowed assessment of millions of parameter sets to find one that closely describes the watershed. Calibration by hand cannot evaluate so many alternatives.

Seasonal Evaluation

The model is generally accurate on a daily basis but accuracy is not consistently high in all seasons. Inconsistent seasonal accuracy was a notable feature of calibration (1a). Using multiple stations improved the model, but it did not remove this shortcoming.

Visual inspection of Figures 5.4, 5.5, and 5.6 does not reveal a pronounced difference in accuracy among seasons and flow conditions, but numerical analysis shows notable patterns. Table 5.5 shows the accuracy of seasonal cumulative flows. For reference, it also includes the errors from calibration (1a). Table 5.5 uses the same format as Table 5.2. It presents the mean and median annual seasonal errors that are calculated from seasonal total flow. The errors are the fractional differences between the sum of daily observed flows over the whole season and the sum of daily simulated flows over the whole season. Errors that exceed TDEC's targets are in bold numerals.

Table 5.5 reinforces the conclusion that using multiple weather stations allows much more effective parameter estimation over using a single station. For highest and lowest flows and for almost every season the errors during the calibration period are much lower here than they were in calibration (1a). For most values in the table, the present calibration also notably improves accuracy during the validation period.

An apparent exception to the improved seasonal performance is in the fall. The mean annual error increases during the calibration period and both mean and median annual errors increase during the validation period. This deterioration is not worrying because it is simply an artifact of the metric. During the calibration period a higher error in a single year drives up the average. The median error is lower when using the composite weather. Both mean and median errors during validation increase in this calibration, but this is also simply an artifact of the metric. The predictions are actually more accurate on a daily basis; the daily fall N-S during validation improved to 0.89, up from 0.77 for calibration (1a). Comparing Figure 5.6 from this calibration with Figure 5.3 from calibration (1a) explains the apparent inconsistency and illustrates a principal weakness of using seasonal metrics. Both calibrations overpredict flows in October and November of 1997. Figure 5.6 shows that calibration (1b) recovers in December,

predicting flow relatively well. The model thus overpredicts flows for the season as a whole. But as shown in Figure 5.3, calibration (1a) noticeably underpredicts December flows. When these underpredictions combine with the overpredictions from October and November, the errors cancel out and make predictions for the season as a whole seem accurate.

Despite the overall improvement in seasonal model performance, Table 5.5 reveals that the prominent seasonal pattern in the errors remains. The model predicts high flows very accurately, as shown by the low errors in the 10% highest flows and in the winters and springs. The mean and median years in the calibration and validation periods easily achieve the TDEC targets for these metrics. The model's accuracy in predicting high flows must be qualified, however. Table 5.6 shows the errors in total volume for highest flows in each year of calibration and validation. The table compares simulated and observed mean daily discharge averaged over the 36 days with highest flows in each year. Errors that exceed the TDEC targets are highlighted in bold numerals. While simulation of the 10% highest flows is generally accurate, there is a pattern in the errors: 14 of the 16 calibration years are underpredictions. This implies that the watershed is "flashier" than the model estimates; the model puts too little water into the stream quickly enough during large storm events. As with the autocorrelation of errors, systemic and consistent errors imply a deficiency in the model. A partial explanation for the underpredictions is that VenSWM does not include a component to describe impervious area. Instead of routing some water from a large storm directly to the stream, the model routes the water to subsurface storage. Subsurface processes delay the water's entry to the stream and evapotranspiration reduces its volume. The model structure might contain other deficiencies that prevent the model from putting enough water into the stream quickly enough. For example, the model components that describe subsurface moisture storage might not adequately reflect soil depth. Then the model would be unable to accurately link watershed response to varying intensities of precipitation and amounts of antecedent moisture.

Figures 5.4, 5.5, and 5.6 show that estimating parameters using multiple weather stations greatly reduces errors in simulating low flows. Nevertheless, this calibration

remains inaccurate for these conditions. Table 5.5 shows that mean and median annual errors in the summers and 50% lowest flows greatly exceed the TDEC target. The fractional errors overstate the inaccuracy of the model, however. The table shows annual mean and median values; some years were very accurate. Table 5.7 shows the errors in total volume in the summer and for the 182 dates with lowest flows in each year. As with Table 5.6, it shows mean daily discharge averaged over the dates of interest. Seven of the 16 calibration summers have errors less than the target of 0.30. While only one year of lowest flows meets the 0.10 target, several are fairly close, for example 1985 and 1991. Fractional errors also overstate inaccuracy in predicting low flows because the fractional errors work off a small base. As seen in Table 5.6, especially in the summer of 1983 and the 50% lowest flows of 1980, a large fractional error can occur even if the absolute error is relatively small. This fact also shows that fractional errors can be "gamed" (accepting less accurate results simply because they better satisfy the statistical limitations of the evaluation metric) if included among the evaluation criteria used to calibrate the model. They would encourage the VenSWM parameter estimation procedures to underpredict low flows because fractional errors for underpredictions can never be greater than one, while overpredictions can produce large fractional errors.

There are potential policy implications related to the overpredictions of low flows. In some watersheds pollutant loadings are highest when less water is present to dilute the pollution (TDEC, 2000b). If the model overpredicts the amount of water in the stream during these conditions, it would underpredict the pollutant concentration in the stream. TMDLs developed with these underpredictions might not dictate sufficient pollutant reductions to make the stream meet water quality regulations. In many streams the magnitude of the pollution problem far exceeds the magnitude of the overpredictions from this model (TDEC, 2000b; TDEC, 2002b; TDEC, 2002c). But in streams that are closer to the threshold, inaccurate predictions of low flows could allow TMDLs that require insufficient pollution reductions.

Despite the inaccuracy in predicting low flows, there are several positive things about this calibration's predictions. Because it used an evaluation criterion based on day-to-day accuracy, it does not "game" the metric. Systematic underpredictions would have

lower fractional errors, but would cause autocorrelation of errors that would indicate an inadequate model. The calibration still shows autocorrelation of errors, but it is much less pronounced than it would have been if the calibration had "gamed" the metric. Another encouraging sign is that the accuracy during the validation period compares favorably with that of the calibration period. There may be a hydrologic factor in the watershed that the model structure does not account for and that causes the systematic overpredictions. If this were the case, the model's consistency suggests that this factor could be addressed outside the model. For example, if measured flows are reduced by water withdrawals for irrigation, the volume of irrigation water could be manually added to simulated discharge before comparison with measured discharge. The final positive thing about these results is that the seasonal and highest and lowest flow metrics were not included in the payoff function used to calibrate the model. It is conceivable that the model could meet the TDEC targets if those targets were included among the calibration criteria.

(1c) Emory River Calibration Using TMDL Evaluation Criteria and Composite Weather

As discussed in Chapter 4, the day-to-day metric seems to be most appropriate for evaluating the quality of model predictions, but the TMDL criteria give practical importance to consideration of seasonal and annual metrics. That calibrations (1a) and (1b) show systematic patterns in seasonal prediction accuracy provides an additional motivation for using the TMDL criteria to perform the calibration. Because the TMDL criteria specifically include metrics that reward accurate prediction on a seasonal basis and low flows, I hypothesized that calibrating the model to maximize performance on the TMDL criteria would reduce the systematic errors encountered in the previous calibrations. I again calibrated a VenSWM model of the Emory River, this time using the TMDL metrics discussed in Chapter 4. I included the six weather stations, and the VenSWM estimation procedures re-estimated the weight each station should receive to maximize accuracy as measured by the new criteria.

Using the seasonal evaluation criteria did not remove the seasonal pattern from the simulation accuracy. Figure 5.7 shows simulated and observed discharge at the

Oakdale gage during the 16-year calibration period. Figure 5.8 zooms to the last three years, which are representative of accuracy for the entire period. As before, the graphs use a logarithmic scale. The pink line is measured discharge and the blue line is simulated flow. The most obvious feature of the predictions is that the lowest predicted flows in this calibration are much lower in the summers than they were in the previous calibrations. The logarithmic scale makes this especially visible, with simulated discharge falling below 0.028 m^3/s (1 ft^3/s) on 690 days during the calibration period.[23]

This calibration is less accurate on a daily basis than calibration (1b). Of course, the reduced daily accuracy is true by definition because the current calibration tried to reproduce seasonal and annual volumes, not daily flows. The daily N-S of 0.709 is superior to what is commonly achieved in the HSPF and NPSM literature, but it is a large decrease from the 0.848 of calibration (1b). Accuracy in the validation period is comparable that in the calibration period, as N-S only falls to 0.685. Figure 5.9 shows simulated and observed discharge during validation.

It is not immediately apparent from the graphs, but the statistics reveal that the seasonal pattern in prediction inaccuracy remains. Table 5.8 shows the accuracy of seasonal cumulative flows from this calibration. For comparison, it includes the errors from calibration (1b). The table uses the same format as Tables 5.2 and 5.5, presenting the mean and median annual errors in total volumes. Errors that exceed TDEC's targets are in bold numerals.

Summer and low flow errors are much lower than they were in calibration (1b), but they still do not meet the TDEC targets. There is very little change in accuracy compared to calibration (1b) for the other seasons and the highest flows. Table 5.9 presents the annual values used to compute the mean and median errors in the summers and for high and low flows. Using the seasonal criteria for calibrating the model does not eliminate the tendency to underpredict high flows and overpredict low flows.

Table 5.10 presents the parameter values estimated by the current calibration and by calibration (1b). The only notable differences are KVARY, INTFW, and IRC.

[23] Figures 5.7 and 5.8 show these extremely low flows when the "Simulated" line falls below the minimum value shown on the y-axis.

KVARY adjusts seasonal groundwater recession, so it is not surprising that using a seasonal payoff function changes this parameter. The higher value means that groundwater recedes more quickly here than in calibration (1b). The calibrations using the daily evaluation criterion were unable to match the quick recession of flow from late spring into early summer. Figures 5.8 and 5.9 show that the high KVARY helps the current calibration mitigate that problem (although it sacrifices daily accuracy). INTFW and IRC regulate interflow recession, which works on the time scale of individual storms (USEPA, 2000). Higher values for these parameters increase prediction accuracy of receding seasonal flows. But the lower daily N-S for this calibration shows that these values are less suitable than those of calibration (1b) for predicting daily stream response to individual storms. The most notable change in the weather station weightings between calibrations (1b) and (1c) is increased weight on Kingston. Kingston generally receives less precipitation than the other stations, so the estimation procedures maximized accuracy in predicting low flows by effectively reducing the estimate of precipitation throughout the watershed.

Even after assessing millions of parameter sets to maximize seasonal and high and low flow accuracy, the VenSWM estimation procedures were unable to greatly improve performance as measured by the TMDL criteria. The overpredictions of low flows experienced in the previous calibrations remained, even though the evaluation criteria placed more weight on accuracy for summer than for other seasons. As a final attempt to reproduce low flows, I ran a further calibration using the TMDL criteria that tripled the weight on spring prediction accuracy. This change attempted to improve summer and low-flow simulation by obtaining the best possible characterization of antecedent moisture entering the summers. Summer and low-flow accuracy increased only slightly and accuracy fell sharply in the other seasons and for high flows. The inability of the model to avoid overpredicting low flows is evidence that there is a hydrologic phenomenon in the summers that is not represented in the model.

Causes of Summer Prediction Inaccuracy

The calibrations discussed above generally provide very accurate predictions on a daily basis. The exceptions are for summers and lowest flows. These errors are related because lowest flows generally occur in the summers. The poor summer performance could be due to modeling or hydrologic issues. From a modeling perspective, the model is inaccurate in a consistent way; it regularly overestimates low flows, no matter what calibration criteria are used. This pattern could occur because the model structure is inadequate to represent the natural system. This explanation seems unlikely given that VenSWM is accurate in other seasons. From a hydrologic perspective, the poor summer performance could be related to the fact that the summer discharge of the Emory River has very low correlation with precipitation. The watershed might contain unique phenomena in the summers that are reflected in the output data but are not captured by the model structure or the input data.

The summer discharge of the Emory River shows a chaotic relationship with summer precipitation. Figures 5.10-5.13 plot cumulative seasonal discharge at the Oakdale gage against seasonal precipitation. The x-axis is the total precipitation in the season. It is derived from VenSWM composite weather file from calibration (1b), which used the day-to-day evaluation criterion. The y-axis is the mean daily discharge averaged over the season. Each point on the graphs represents one year between 1980 and 1998.[24] In the fall, winter, and spring, discharge shows a relatively direct relationship with precipitation. Some scatter exists around each regression line because unique rainfall characteristics and watershed conditions mean that not all precipitation events have the same effect on stream discharge. One role of models is to predict how the different conditions affect discharge. However, no model could explain the extreme scatter in the relationship between summer precipitation and discharge in the Emory River. The R^2 in the summer is only 0.57, much lower than in the other seasons.

The most likely explanation for the chaotic pattern is that measured precipitation is less representative of watershed conditions in the summer than it is in other seasons. In

[24] Note that the summer graph uses a different y-axis scale from the other seasons. The low flows require a different scale to show the relevant pattern.

the other seasons, frontal activity likely causes much of the precipitation in the watershed. Frontal storms cover large areas and would be measured at several weather stations, allowing the composite weather input to adequately depict the storm's magnitude throughout the watershed. Frontal activity occurs in the summers, but so do convective storms. The sparse network of measurement points around the Emory River watershed would not capture all localized convective storms in the summers. But unmeasured storms still increase stream discharge. A predictable relationship would exist between measured discharge and actual precipitation, but the rainfall measurements would not reflect actual precipitation.

Figures 5.14-5.17 support this hypothesis. While Figures 5.10-5.13 plotted discharge against precipitation from the composite weather file, Figures 5.14-5.17 use the precipitation measured at Monterey. It is important to remember that these figures show only *measured* data; there is no model involved. Each seasonal correlation is lower when using data from a single station, but the deterioration is especially high in the summer. Using multiple measurement sites only modestly improves the characterization of frontal storm activity in all seasons. But using several stations also greatly improves the characterization of convective storms in the summers. At least one of the stations is likely to capture a localized storm. The improvement would have been especially striking if the VenSWM estimation procedures had weighted the data from the various stations to match individual storms.

It is also possible that limitations in the discharge measurements explain some of the apparent randomness in the summer precipitation-discharge relationship. An apparently chaotic relationship would exist if measured discharge were less accurate for low flows than for higher flows, even if measured precipitation were perfectly representative of conditions throughout the watershed. This explanation is unlikely for the Emory River. There is only one case in the three watersheds where discharge volume affects measurement accuracy, and measurements are less accurate for *high* flows in Crooked Fork in 1967 (USGS, 1967).

Besides being inaccurate, the summer predictions have a shortcoming that is more related to modeling goals than to hydrologic goals. The errors are *consistent*; the model

regularly overpredicts low flows. One possible explanation is that the weather stations used in the model are more prone to convective storms than the rest of the watershed. If this were true, data from the stations would imply that the overall watershed gets more rain than it really does. This seems unlikely given that none of the stations are on the northeastern side of the watershed, where high relief should make convective activity most frequent.

Agriculture could also cause summer overpredictions. Measured discharge would be reduced by irrigation and livestock watering, especially in the summers. But VenSWM would not remove water used for these purposes because it does not have an irrigation component. This is a shortcoming of the model structure. It is not a major factor in this case, however, as surface water use for irrigation and livestock watering in the Emory River watershed averaged only 0.03 m^3/s in 1990 and 0.06 m^3/s in 1995 (USGS, 2003b). These are averages spread throughout the year, however, and presumably most of this use occurred in the summers. But even assuming that *all* of the use in the year occurred in the summer (i.e., quadrupling the daily rate) would only account for a small part of the overpredictions. There is also nonagricultural irrigation in the watershed. Crossville calls itself the "Golf Capital of Tennessee;" watering golf courses has the same effect on discharge as agricultural irrigation does. The lower zone evapotranspiration parameter (LZETP) in VenSWM should partially account for water lost to irrigation. LZETP uses monthly values, so higher values in the summer would compensate for the absence of a specific irrigation component in the model.

Domestic water supply may also help explain the overpredictions. The majority of homes in the watershed use septic systems (TDEC, 2000a), so water diverted for domestic uses is not directly returned to the stream. Crossville's population and water demand are both growing rapidly. Averaged over the year, diversion of surface water for public water supply increased from 0.24 m^3/s in 1990 to 0.28 m^3/s in 1995 (USGS, 2003b). Additionally, TDEC inventories 47 dams in the Emory River watershed that are 20 feet or higher and impound at least 30 acre-feet of water (TDEC, 2000a). Dams alter the timing of stream discharge by storing and releasing water at different times. The dams are less likely to release incoming water in the summers, further driving down

summer discharge downstream. Dams also decrease discharge because stagnant water with high surface area increases evaporation. These factors do not explain the magnitude of the overpredictions, but reveal that the errors are not quite as large as they first appear.

In summary, each of the VenSWM models of the Emory River is generally accurate in predicting discharge. The exception is for low flows and summer flows. Inaccuracy for these conditions may be caused by factors that are outside the scope of what the model or the data capture. I therefore concluded that calibration (1b), which used a composite weather input and a day-to-day evaluation criterion, adequately estimated the characteristics of the Emory River watershed and characterized its hydrology. To test how well these parameters transfer across scales, I turned to the subwatersheds.

(2a) Applying the Emory River Parameters to the Daddy's Creek Subwatershed

The Daddy's Creek watershed has similar physical characteristics to the larger Emory watershed. It is also largely in the same ecoregion as most of the Emory watershed. I therefore expected that the estimated characteristics of the Emory River watershed would be good estimates of the characteristics of the Daddy's Creek watershed. My results supported this hypothesis. I applied the parameters from calibration (1b) to a model of the Daddy's Creek watershed that simulated discharge at the gage near Hebbertsburg between October 1, 1999, and September 30, 2001.

I changed only a few of the Emory River watershed parameters before applying them to the Daddy's Creek watershed. I measured the length and slope of the overland flow plane specifically for the Daddy's Creek watershed and used these values instead of those from the Emory River model. I also changed the weather station weights so that the subwatershed model would use an input that better represented precipitation specifically in the subwatershed. The optimizer calibrated a model with parameters specific to Daddy's Creek (see calibration (2b) below). Table 5.11 shows these weather station weights. For comparison, the table also shows the weights for the two Emory River models that used composite weather. The Daddy's Creek watershed is on the western side of the larger watershed, so it is unsurprising that its model contained much

lower weights for stations on the eastern side of the watershed (Kingston and North-to-West weight).[25] Despite the low weights of the eastern stations and their distance from the Daddy's Creek watershed, I chose to retain them in the model because they are still relatively close to the subwatershed. They also provide a spatial spread of measurement points to help capture unique weather patterns that occur in the Daddy's Creek watershed but may not be measured at the closely spaced western stations.

Figure 5.18 shows simulated and observed mean daily discharge at the Hebbertsburg gage. Visually, the Emory River parameters appear to do an excellent job of simulating discharge in Daddy's Creek. The blue line shows the model predictions and the pink line shows measured discharge. As with the previous discharge graphs, Figure 5.18 uses a logarithmic scale to better show high and low flows. Flows are much lower in Daddy's Creek than in the Emory River, but they generally show the same seasonal pattern. Higher flows tend to occur in the winters and lower flows tend to occur in the summers.[26] The statistics support the visual accuracy of the predictions. The daily N-S is 0.805, which is comparable to the accuracy these parameters achieved in the Emory River model (0.848 for calibration and 0.825 for validation). That the accuracy is both high and similar to that in the Emory River model implies that the Emory watershed parameters adequately estimate the physical characteristics of the Daddy's Creek watershed.

The parameter set shows a seasonal pattern in prediction accuracy similar to that for the Emory watershed. Table 5.12 shows the fractional errors in total discharge in each of the two modeled years. Errors that exceed the TDEC targets are in bold numerals. On a seasonal basis, the Emory parameters generally yield accurate predictions for Daddy's Creek. Six of the eight seasons meet the TDEC goals. But these parameters underpredict highest flows and overpredict lowest flows in the subwatershed. The summer error is acceptable (and even a rare underprediction) in the first year, but the

[25] The other weather station parameters only determine the relative influence of one station in a set of stations.

[26] The low fall flow in 2000 is an anomaly. The full data history for the Hebbertsburg gage includes data from 1957 to 1968. Including these data, mean daily discharge averages 1.67 m^3/s during the summer months, 6.11 m^3/s during the fall months, and 13.9 m^3/s during the winter months.

usual large overprediction appears in the second year. The overprediction is especially notable because the model greatly underpredicts large storms in late July and early August. The Emory River parameters have trouble reproducing the receding flows from late spring into summer in Daddy's Creek, just as they did in the larger watershed. This pattern is especially noticeable in the second year, although some of the inaccuracy is due to a large error in predicting response to a single storm in late May.[27]

These patterns of errors are familiar from the Emory River models, but two new patterns emerge when applying the parameters to the Daddy's Creek watershed. Underpredictions of 10% highest flows in the subwatershed are more pronounced than they were in the larger watershed. The Emory River models consistently underpredicted highest flows by a small amount. The Daddy's Creek watershed receives somewhat less precipitation than the overall watershed, so it is not surprising that the Emory parameters underpredict to a greater extent in a model of a drier subwatershed. Using the Emory parameters for the Daddy's Creek watershed seems to introduce another notable error, a large fall overprediction in the first year. Figure 5.18 shows that this error is not especially troubling because it is the result of overpredictions at the very beginning of the simulation period. The overpredictions likely occur because of a poor assumption about the antecedent moisture in the watershed. I had used the ending subsurface storage levels from an earlier calibration of a Daddy's Creek model (see calibration (2b) below) to estimate the initial conditions. These levels were apparently a poor estimate.

Despite using subwatershed-specific weather station weightings, Figure 5.18 suggests that imperfect characterization of precipitation reduced prediction accuracy. Several spikes in spring and summer measured flows do not appear at all in the simulation (e.g., July 13, 2000). They could be due to convective storms that increased flow but that did not strike any of the weather stations. At other times, the weather stations record a precipitation event, but the amount of measured precipitation does not seem to be representative of what the watershed received. For example, the two storms in late July and early August of 2001 send the model from a string of large

[27] Both observed and simulated discharge increase, but they do so with different magnitudes. This difference suggests that an imperfect characterization of rainfall causes the error.

overpredictions to large underpredictions. These storms did not strike all of the weather stations with the same intensity. In the first storm (July 28-30), the western stations recorded 10.6 cm of rain at the Crossville Experiment Station, 9.2 cm at the daily Monterey station, and 7.5 cm at the Crossville Airport.[28] On the eastern side of the watershed, Kingston received 7.7 cm and Lancing received 6.3 cm. This distribution suggests that precipitation was concentrated on the western side of the Emory watershed. The eastern stations have relatively low weights in the Daddy's Creek model, but their lower totals still pulled down the overall input to the model. There are also large local differences, especially between the two Crossville stations.[29] Additionally, the VenSWM estimation procedures (see calibration (2b) below) determined that almost all Crossville weight should go to the Experiment Station, which had much lower precipitation than the Airport in this storm. This weighting might be appropriate in most cases, but it likely under-weighted Crossville rainfall in this event.

The influence of this type of localized rainfall was not especially noticeable in the calibrations of the Emory River model. In the storm from July 28-30, 2001, particularly heavy rainfall in some areas of the Emory watershed, like around the Crossville Experiment Station, would have offset lower rainfall in other areas, like around Lancing. But the smaller size of the Daddy's Creek watershed means that exceptionally high or low rainfall in a small area is less likely to be canceled out by the amount of rainfall received in other small areas in the watershed. The reduced averaging increases the importance of establishing an accurate characterization of precipitation. Determining representative rainfall is more difficult over smaller areas because they are less likely to have a complete matrix of measurement locations.

(2b) Calibrating a Model Specifically for the Daddy's Creek Watershed

Calibrating parameters in a model specifically of the Daddy's Creek subwatershed provides the best possible VenSWM estimate of the subwatershed's physical

[28] Several hours were missing from the data from the hourly Monterey station data, so it is not included here.

[29] The comparison spans several days, so the different reporting periods for the two Crossville stations were not a factor. The extreme difference between them raises questions about data quality.

characteristics. I calibrated such a model for the period from October 1, 1999, and September 30, 2001. The accuracy of this calibration is directly comparable to that of scenario (2a), which used the Emory parameters to estimate the characteristics of the Daddy's Creek watershed. The two parameter sets provide similar accuracy in predicting subwatershed discharge. This result fit my expectations because the two watersheds have similar physical characteristics.

Figure 5.19 shows that the subwatershed-specific parameters provide only a modest improvement over scenario (2a) (compare to Figure 5.18). The blue line shows the model predictions and the pink line shows observed discharge. The subwatershed-specific parameters do offer a slight improvement in daily accuracy, as the N-S increases to 0.851, up from 0.805 using the Emory parameters.[30] The improvement is largely due to better simulation of high flows, which is difficult to perceive on the logarithmic scale of the graph.

The subwatershed-specific parameters also provide only a modest improvement in seasonal accuracy. Table 5.13 compares the simulation accuracy of the two parameter sets in predicting discharge in Daddy's Creek, as measured by the TMDL criteria. It shows fractional errors in total volume for each of the two modeled years. Values that exceed the TDEC targets are in bold numerals. The two parameter sets are similarly accurate when assessed with these metrics and neither set is obviously superior. The subwatershed-specific parameters are slightly more accurate for high flows, reflected by their higher N-S and lower errors in 10% highest flows. Both parameter sets have high fractional errors when predicting low flows.

Using parameters specifically estimated for the Daddy's Creek watershed does not eliminate the seasonal patterns of errors produced by the Emory parameters. Parameters estimated specifically for the subwatershed still overpredict low flows, underpredict high flows, and have trouble reproducing the receding flows from late spring into summer. That the Emory parameters do not adequately reflect the physical

[30] The improvement is true by definition when evaluated by the criteria used to calibrate the model (in this case, mean daily discharge). The VenSWM evaluation procedure obtained the Emory parameters with no knowledge of subwatershed discharge, so only a grossly inadequate subwatershed calibration would provide less accurate predictions of subwatershed discharge.

features of the Daddy's Creek watershed was a possible explanation when these patterns appeared in scenario (2a). But the fact that the errors produced by the subwatershed-specific parameters show the same patterns weakens this argument. Nevertheless, the Daddy's Creek parameters do provide a noticeably better characterization of stream behavior in some cases. The best example is the storm from July 28-30, 2001. The Daddy's Creek model uses the same imperfect weather characterization as the previous scenario. But comparing Figure 5.19 with Figure 5.18 shows that the subwatershed parameters yield much more accurate predictions of the peaks in discharge. At other times the Emory parameters actually seem to do a better job than the Daddy's Creek parameters. For example, the Emory parameters provide better predictions of the peak and recession in flows from the storm on September 27, 2000.

Besides providing an adequate depiction of the physical characteristics of the Daddy's Creek watershed, the Emory parameters may be more robust in predicting future subwatershed flows than Daddy's Creek's own parameters. The Emory parameters are based on 16 years of calibration, while the Daddy's Creek parameters are based on only two years. Two years is insufficient time to fully assess whether a parameter set will produce accurate predictions in a range of watershed and climatic conditions. Because the Emory parameters were robust across the 19 years of data in that watershed and because they were generally accurate during this two-year period in the subwatershed, we can be confident that they would produce similar accuracy in predicting future flows in Daddy's Creek.

Robustness in predicting future flows is more likely when parameters adequately describe the physical characteristics of the watershed. Table 5.14 shows the Emory River and Daddy's Creek parameters. All of the Daddy's Creek parameters are within the range that I determined to be realistic given the physical characteristics of the subwatershed and they are within the bounds of what has been used in HSPF and NPSM modeling. Nevertheless, the Emory parameters may actually be more consistent with the characteristics of the Daddy's Creek watershed. At least one of the values for a Daddy's Creek parameter that directly reflect physical characteristics is curious. The lower zone evapotranspiration parameter (LZETP) is much lower for the Daddy's Creek watershed

than it is in the Emory watershed. LZETP is largely influenced by land use (USEPA, 2000). Somewhat lower forest cover in the subwatershed (77% versus 88%) suggests that a slightly lower LZETP in the subwatershed is appropriate. But the magnitude of the difference is surprising, especially since watered golf courses and lawns in the subwatershed should increase evapotranspiration over what land use alone suggests.

Several explanations for the lower LZETP in the Daddy's Creek watershed are possible. It may be the guidance is mistaken and that land use is not the fundamental driver of LZETP. The extensive modeling experience in diverse regions discourages this conclusion. Another explanation is that the calibrated parameters for both watersheds are accurate; the unexpected results may simply be due to unmeasured or poorly measured characteristics. For example, land use between the two watersheds might not be as comparable as the data suggest. The land use data were collected in the mid-90s, but the subwatershed model estimated LZETP using discharge data from 1999-2001. The Crossville area urbanized rapidly in the late 1990s, so the true land use in the subwatershed during the modeled period might be less forested and more urban. This would justify a lower LZETP for the Daddy's Creek subwatershed. Urbanization over just a few years seems unlikely to explain a difference of such magnitude between the Emory and Daddy's Creek LZETP values. More likely, one of the values does not accurately represent the physical characteristics of its watershed. The Daddy's Creek parameters provide a good fit with the discharge data for this two-year period, but the short calibration period discourages the conclusion that they are an ideal representation of the physical characteristics of the subwatershed. Because of their long data history, demonstrated robustness, and apparent ability to describe the physical characteristics of the Emory River watershed, the Emory parameters (including LZETP) are reliable indicators of the characteristics of that watershed. Their accuracy during this two-year period suggests that they are also a suitable estimate of the characteristics of the subwatershed.

(3a) Applying the Emory River Parameters to the Crooked Fork Subwatershed

The Crooked Fork subwatershed has somewhat unique physical characteristics from the rest of the Emory River watershed. I hypothesized that the parameters that estimated the characteristics of the Emory watershed would provide a fair estimate of the characteristics of the Crooked Fork watershed, but that a much better depiction would be possible. I also expected the Emory parameters to be less suitable for the Crooked Fork subwatershed than they were for the Daddy's Creek subwatershed. My results supported these expectations.

As with the Daddy's Creek subwatershed, I applied the Emory River parameters from calibration (1b) to the Crooked Fork subwatershed. The model predicted discharge at the gage near Wartburg for the period from October 1, 1966, through September 30, 1968. Also as I did for Daddy's Creek, I changed the Emory parameters by measuring subwatershed-specific values for the length and slope of the overland flow plane.

I also used subwatershed-specific weather station weightings (see calibration (3b) below). Table 5.15 shows these weightings. For reference, it also shows the weights from the Emory River and Daddy's Creek models. Figure 5.20 gives a graphical depiction of the weightings. As expected, the North-to-West weight is higher than in the other models. This increases the influence of the data from Sunbright, which is closer to Crooked Fork than the other stations.[31] The western stations might not be expected to accurately represent precipitation in the Crooked Fork watershed. But I included them because they are closer to the watershed than any other weather stations and can help capture localized precipitation variability that might not be measured at a single weather station (Sunbright). They also helped complete the large amount of missing data from the Sunbright records.

Figure 5.21 shows simulated and measured discharge at the Crooked Fork gage near Wartburg. Predicted discharge matches measured discharge fairly well, but the Emory parameters noticeably underpredict high flows, especially in the fall seasons. The N-S reflects the fact that high flow predictions are less accurate than in calibrations (1a) through (2b). The daily N-S here is 0.678, which is higher than is commonly achieved in

[31] The Lancing station did not begin to record data until 1989, so it was unavailable for this model.

the HSPF and NPSM literature but much lower than the 0.805 these parameters yielded in Daddy's Creek. The graph seems to show that the characterization of precipitation is adequate because there are few instances of large uncorrelated movements between measured and predicted flow.

Table 5.16 shows the seasonal fractional errors in the two modeled years. For reference, it includes the performance of the Emory parameters in Daddy's Creek. Errors that exceed the TDEC targets are in bold numerals. The Emory parameters are less accurate for Crooked Fork than they were for Daddy's Creek but they still perform fairly well. Errors exceed the TDEC targets in four of the eight seasons, but several of the errors only miss the 0.30 target by a small amount. Interestingly, this calibration represents the first time the model accurately profiles low flows. This is not a cause for celebration, however. Figure 5.21 shows that the apparent accuracy is the result of overpredictions and underpredictions canceling each other out.[32] In the first year, underpredictions that dominate the fall and winter are offset by overpredictions in spring and summer. In the second year, overprediction of receding flow from late spring into summer is offset by earlier winter underpredictions.[33] This cancellation of errors is another example of the limitations of using seasonal metrics for evaluating model performance.

(3b) Calibrating a Model Specifically for the Crooked Fork Subwatershed

As I expected, estimating parameters specifically for Crooked Fork noticeably increases daily simulation accuracy. I calibrated a model to predict discharge at the gage near Wartburg between October 1, 1966, and September 30, 1968. Figure 5.22 shows the predicted and observed flows. Visual comparison of Figures 5.21 and 5.22 does not immediately reveal that the subwatershed-specific parameters provide a large

[32] Basing the lowest flow metric on half of the days in the year is probably necessary in some regions of the country where flow of many streams will be zero for much of the year. But including so many days in the evaluation in a humid area like eastern Tennessee might not adequately characterize the accuracy of simulating the very lowest flow conditions.

[33] It is important to remember that the logarithmic scale visually overstates the overpredictions. This is especially relevant in the late spring and early summer of the second year, when flow is extremely low. Measured discharge falls below 0.028 m^3/s (1 ft^3/s) for 26 of the 92 days that summer.

improvement, but close inspection shows that predictions of high flows are more favorable. This is reinforced by the increase in daily N-S from 0.678 to 0.803.

Table 5.17 also supports the idea that the subwatershed-specific parameters improve prediction of high flows. It shows fractional errors in total volume in each season of the two years and for high and low flow conditions. Errors that exceed the TDEC targets are in bold numerals. Predictions of the 10% highest flows are much more accurate in both years using the subwatershed-specific parameters. However, the subwatershed-specific parameters are much less accurate than the Emory parameters for predicting the 50% lowest flows. The daily evaluation criterion used to estimate parameters for the subwatershed rewarded accurate prediction of high flows at the expense of prediction of low flows. But we should not overstate the importance of the relatively high fractional errors. The absolute errors are actually low, but the fractional errors use an extremely low base. Ninety-eight days in the two-year calibration period had mean daily discharge under 0.14 m^3/s (5 ft^3/s). On a seasonal basis, the Crooked Fork parameters provide only modestly more accurate predictions than the Emory parameters.

An important feature of Table 5.17 is that the Crooked Fork parameters show very different accuracy in the two years. The variability occurs because the two modeled years have very different flow conditions. Table 5.18 reproduces the fractional errors and shows mean daily discharge in each season. Discharges in the fall and spring are much higher in the second year than in the first year (101% and 78%, respectively), but discharge in the first summer is almost 50 times higher in the first year. The model has difficulty reproducing this variability and seasonal errors vary widely. There is a large overprediction in the first spring and a large underprediction in the second spring. There is a large underprediction in the first summer and a large overprediction in the second summer. Only errors in highest flows (the most important aspect of the evaluation criterion used to estimate the parameters) remain relatively constant.

The variability in prediction accuracy occurs because two years are insufficient to properly evaluate the quality of a model and its predictions. A range of conditions during calibration normally aids indirect measurement and parameter estimation. But when

there is little time under each condition, the procedures that estimate parameters cannot determine what combination of parameters best characterizes stream response for that condition. Table 5.17 showed that the Emory parameters provided somewhat less accurate predictions than the subwatershed-specific parameters and that prediction accuracy was similarly variable between the two years. But since the Crooked Fork parameters were estimated using only two years of data (moreover, two years with diverse flow conditions), we cannot be confident of their robustness in predicting future discharge or in the adequacy of their depiction of the physical features of the watershed.

The longer calibration period for the Emory River parameters means that they are a good estimate of the physical characteristics of the larger watershed. Comparing their values with the Crooked Fork parameter values suggests that they might even reflect the characteristics of the Crooked Fork watershed more accurately than the subwatershed-specific parameters (see Table 5.19). The Emory parameters provide reasonably accurate predictions in the subwatershed, so they seem to be at least a decent estimate of the subwatershed characteristics. Additionally, it is surprising that LZETP is the same in the Crooked Fork subwatershed as it is in the Daddy's Creek subwatershed and that it is lower than in the Emory River watershed. Crooked Fork is much more heavily forested than either of those watersheds, which implies that a higher LZETP is appropriate. The Crooked Fork watershed has similar cropland and urban area to the other watersheds, so the influence of agriculture or domestic water consumption should affect all watersheds equally and be reflected in the LZETP of each. As mentioned above, one possible explanation is that the land use data do not represent watershed conditions during the modeled period. The land use data are from the mid-1990s, but the model estimated parameters for the late 1960s. A more detailed investigation of land use in during the modeled time might show that lower LZETP would be appropriate for the Crooked Fork watershed. Strip mining was more prominent in the watershed during the 1960s than the 1990s and strip mines would greatly reduce vegetated area and increase surface runoff. Both of these factors would decrease evapotranspiration and, by proxy, LZETP. But the short calibration period covering diverse flow conditions means that inadequate parameter values are the most likely cause of the unexpected values. But it is

encouraging that INFILT, another parameter that has a direct basis in physical characteristics, is notably higher in the Crooked Fork watershed than in the Emory watershed. This reflects the fact that the Crooked Fork watershed has more high-permeability soil than the larger watershed. The unique physical characteristics of the Crooked Fork subwatershed mean that it is not surprising that some parameters estimated specifically for it are more appropriate than those estimated for the Emory River watershed.

Chapter 6 Conclusion

My results suggest that transferring the parameters from a hydrologic model across scales holds promise. Before beginning my research, I hypothesized that the parameters that estimate the physical characteristics of the large Emory River watershed would adequately estimate the characteristics of two of its subwatersheds, Daddy's Creek and Crooked Fork. My results support this hypothesis. The Daddy's Creek subwatershed has similar physical characteristics to most of the rest of the Emory watershed, and subwatershed-specific parameters provide only a very modest improvement (an increased Nash-Sutcliffe R^2 of 0.05) in the model's accuracy in predicting stream discharge in the subwatershed. The Crooked Fork subwatershed has somewhat distinct physical characteristics from much of the rest of the Emory watershed, but the Emory parameters still provide reasonably accurate discharge predictions there. Using Crooked Fork-specific parameters only increases the Nash-Sutcliffe R^2 by 0.12.

My results also indicate that characterizing precipitation is as important as characterizing the physical attributes of the watersheds. Discharge predictions are much more accurate when using a composite weather input instead of data from a single weather station. A hydrologic model will not produce accurate predictions if its driving input data, precipitation, do not adequately represent the true precipitation in the watershed. Determining representative precipitation is also a problem of scale because precipitation often varies on local scales. Two factors facilitate the characterization of precipitation, and both encourage modeling larger areas. One factor is an adequate matrix of measurement locations, because a dense network of weather stations is more likely to capture local variability than a sparse network. The second factor is the degree to which a stream's discharge averages the amount of precipitation that falls inside the boundaries of its drainage area. It is easier to estimate precipitation when areas in the watershed with exceptionally low precipitation are countered by areas with exceptionally high precipitation because measurement points do not need to record exceptional conditions. Both of these factors encourage modeling larger areas. Larger areas are more

likely to have multiple precipitation measurement locations and are less affected by very localized precipitation that is unlikely to be captured at individual measurement points.

These results could have implications for modeling small watersheds. Small watersheds frequently do not have sufficient precipitation and discharge data to calibrate robust models of their hydrology. But sufficient data usually exist for larger watersheds. My results suggest that it may be viable to transfer characteristics estimated for a data-rich large watershed to its data-limited subwatersheds, even when the subwatersheds have somewhat distinct physical characteristics from the rest of the watershed. I found that the accuracy of the Emory parameters was noticeably lower in the physically unique subwatershed, however, which raises the caution that transfer across scales is not universally viable. But the physical properties that influence watershed hydrology usually change very gradually across space. If we can establish that a small constituent area is at least moderately similar to the larger area, it might be viable to transfer the parameters from a hydrologic model of the larger watershed to a model of the subwatershed.

My results also suggest several ways to improve the accuracy of VenSWM predictions on any scale. The most important is to increase the data resources, especially for precipitation. Even the large Emory River watershed is covered by only a sparse matrix of weather stations. The accuracy of the stream discharge predictions shows that the six stations in and around the watershed allow a decent characterization of precipitation. But many more stations are necessary to gain confidence in the precipitation profile. It would also be desirable to have a greater spatial spread in the weather stations. The scarcity of measurements on the eastern side of the watershed means that any characterization of precipitation for the entire watershed is incomplete. A denser and wider spread of measurement points is especially desirable in the summers, to help capture extremely localized convective precipitation. Establishing representative precipitation in the subwatersheds would also require many more measurement points. Smaller watersheds are more affected by highly localized precipitation, and many points would be necessary to capture this variability. At the least, it would be desirable to have one or more stations within the subwatershed boundaries.

More discharge data in the subwatersheds are also desirable. The discharge measurements in both of the subwatersheds I studied exist over only a short time period. The limited data prevent a robust hydrologic calibration because the discharge data do not cover a wide range of precipitation conditions with diverse amounts of antecedent moisture.

Altering the model structure could also improve hydrologic predictions. There is evidence that processes that are not included in the model affect the hydrology of the Emory River. Domestic water supply and agriculture are potentially important factors that the model does not consider. It is also possible that there are processes in the natural system (i.e., not anthropogenic factors) that the model does not reflect. For example, there may be unmodeled phenomena that cause flows to recede more quickly from spring into summer than the model can reproduce. Additional investigation is warranted to determine whether this is a common problem when modeling other geographic areas with SWM. If it is, it would reveal a flaw in the model structure that would justify further field research to determine what processes are occurring and how best to model them.

Despite the potential limitations of the model structure, VenSWM is a useful tool for hydrologic modeling. I found that the current beta version of LSPC contained many programming bugs. Even when its functionality behaved as designed, it was difficult and time-consuming to use. Implementing SWM in the Vensim environment offers several advantages. The most important is the presence of an optimizer, which allows the evaluation of many more parameter sets than would be possible by calibrating models by hand. Testing more alternatives increases the likelihood that the calibration will find the best possible estimates for the parameters. Vensim also contains many tools that facilitate the analysis and presentation of model predictions.

My experience also emphasizes the importance of establishing a consensus on how to evaluate model predictions. TMDLs use a standard definition for acceptable calibrations. But the seasonal basis of the criteria is not an ideal way to measure model performance because it does not reflect the scale of interest. A daily time scale is likely more valid because it is closer to the time scale over which hydrologic processes occur and over which water pollution endangers aquatic life and human health. But there is no

universal standard of an acceptable level of daily prediction accuracy. To some extent this is justified, as the maximum achievable accuracy depends on the model used and the watershed studied. Nevertheless, greater guidance is desirable. It would also be beneficial if more studies published daily results to allow other modelers to gain a better understanding of the true accuracy of the models.

My results suggest several paths for additional investigation. One is to test parameter transfer in other watersheds. Parameter transfer should be tested in diverse watershed sizes, physiographic regions, and ecoregions. To help bound the amount of extrapolation that is viable, parameter transfer should also be tested in subwatersheds that bear less physical resemblance to their larger watersheds than the two subwatersheds I tested.

Additional work is also warranted in the watersheds I studied. The cause of the summer overpredictions should be established. This would require gathering additional data on domestic, agricultural, and industrial water use in each watershed. Additional land use data should also be gathered for the 1999-2001 period in the Daddy's Creek watershed and the 1968-1968 period in the Crooked Fork subwatershed. These data could help establish whether some of the surprising parameter values I estimated are physically justified.

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Appendices

Appendix A Description of the Stanford Watershed Model Hydrology Modules

Background

The Stanford Watershed Model (SWM) and its Hydrologic Simulation Program FORTRAN (HSPF), Nonpoint Source Model (NPSM), and Loading Simulation Program C++ (LSPC) implementations purport to be physical models that replicate the natural processes that affect stream discharge and pollutant loadings. The algorithms incorporate data from laboratory experiments and empirical relationships from instrumented watersheds among watershed characteristics like weather, land use, soils, and topography (Bicknell et al., 2001). Some have criticized SWM for not being a fully physical model, however. Its parameter definitions are somewhat vague and do not directly reflect watershed characteristics (Heng and Nikolaidis, 1998; Whittemore and Beebe, 2000).

SWM is also not a completely physical model because it simplifies the enormous complexity of the natural processes. It is structured as a system of water flows and storages. The mass balance equation, often called a water budget, governs how the water moves through the system. This equation states that the volume of water entering the system equals outflows plus storage. Mathematically, the mass balance is: Inputs minus Outputs plus or minus Accumulation equals zero. For a given time period, the water budget “accounts for” the amount and location of all water in the system (Wanielista et al., 1997). Despite this simplification, SWM may be considered a physical model because it considers most of the important physical features and processes that govern watershed hydrology. This appendix describes how the model depicts those features and processes.

The Vensim Stanford Watershed Model (VenSWM) reproduces the LSPC implementation of SWM. VenSWM was constructed from the source code to HSPF version 12 (Old Dominion University, 2002). In this Appendix, I present parameters that the modeler can adjust in all capital letters. I present state variables calculated by the model in all lower case letters.

Water Movement through the Stream Channel

To simulate water movement through stream segments, VenSWM uses a fixed transit time. This time is calculated outside the model from a first-order exponential delay based on the stream length, channel slope, and the roughness coefficient of the channel bottom.

Water Movement through and over Land Segments

VenSWM simulates nine hydrologic processes in land segments: interception, surface detention storage, upper zone storage, infiltration, evapotranspiration, interflow, surface runoff, lower zone storage, and groundwater flow. The mass balance equation dictates that their sum must equal the volume of precipitation. LSPC uses six storages to simulate the interactions among these processes. The processes occur simultaneously and affect one another (Bicknell et al., 2001). The storages are interception storage, surface detention storage, interflow storage, upper zone storage, lower zone storage, and active groundwater storage.

Figure A.1 shows how water moves among the VenSWM storages. A time series description of discharge simulation begins with precipitation (supy). VenSWM first subtracts the amount of water that is intercepted by vegetation (cepo), which becomes available for evaporation at a later time (cepe). Water that is not intercepted moves to surface detention storage. From there it runs off to an adjacent downslope land segment or to the stream (suro), moves to interflow storage (ifwo), infiltrates through the soil surface (infil), moves to upper zone storage (uzi), or moves directly to active groundwater storage (agwi). Water that moves to interflow storage will later flow to an adjacent downslope land segment or to the stream (ifwo), where it becomes an input (ifwli) to that segment or the stream. Water that moves to upper zone storage is removed by evapotranspiration (uzet) or percolates (perc) to lower zone storage or active groundwater storage. Water enters lower zone storage directly from surface detention storage or from upper zone storage (lzi is the sum of these flows). Water leaves lower zone storage only through evapotranspiration (lzet). Water enters active groundwater storage either directly from surface detention storage or as percolation from upper zone

storage (agwi is the sum of these flows). It leaves as active groundwater outflow (agwo) to an adjacent land segment or the stream. It can also leave through evapotranspiration (aget) or be lost to deep percolation (igwi). Active groundwater outflow becomes a water input to an adjacent land segment or the stream.

Interception Storage

The first process simulated in a precipitation event is interception, which is the volume of water that does not reach the land surface. In pervious land segments, most interception occurs on vegetation (all land segments in VenSWM are pervious).

Precipitation (supy) is the only input to interception storage. The output (cepo) is the volume of precipitation that exceeds the available interception storage capacity (cepsc). Precipitation decreases available interception storage and evapotranspiration empties interception storage (cepe). I discuss the evapotranspiration simulation below.

There is only one parameter the modeler can adjust to affect interception processes. CEPSC describes the volume of interception storage capacity. Its value depends on the surface characteristics of the land, primarily the type and density of vegetation (USEPA, 2000). Forested areas and areas with dense vegetation generally have high CEPSC (USEPA, 2000). VenSWM does not differentiate among areas with specific land uses, so a weighted average of vegetation type dictates CEPSC. To consider vegetation that loses its leaves in the winter, CEPSC uses monthly values. Higher CEPSC reduces the volume of water available for further hydrologic processes, thus reducing simulated discharge.

Surface Detention Storage

Precipitation that exceeds the available interception storage capacity reaches the land surface and enters surface detention storage. Surface detention storage does not have a precise physical definition. It is simply the amount of water that is subject to infiltration or runoff (Bicknell et al, 2001). It most closely resembles water pooled on the land surface, but it is not available to evapotranspiration. In each time step, water in

surface detention storage remains there, infiltrates to lower zone or active groundwater storage, enters upper zone storage, enters interflow storage, or becomes surface runoff.

Water enters surface detention as precipitation that exceeds interception storage capacity (cepo) or as inflow from an adjacent upslope land segment (surli). There are several ways water leaves surface detention storage. It can enter upper zone storage or interflow storage (discussed below). It can also infiltrate to lower zone storage or active groundwater storage or run off to an adjacent downslope land segment or the stream. Several parameters interact with the saturation of subsurface storages to dictate how VenSWM allocates surface detention storage among these fates. I discuss those parameters and subsurface storages below.

Infiltration

Soil permeability and soil saturation are the most important determinants of the volume of water that infiltrates through the soil surface (infil). VenSWM has several parameters that describe these factors. Soil permeability is determined from a soil permeability index parameter (INFILT) and a linear probability density function (determined by the parameter INFILD). INFILT corresponds with soil characteristics that determine permeability, but it does not directly reflect measurable infiltration rates (USEPA, 2000). Higher INFILT causes additional water to enter lower zone storage and active groundwater storage, which increases the base flow of the stream. Lower INFILT leaves more water on the surface and increases runoff. INFILD governs a linear probability density function governed that accounts for spatial variation in permeability rates. INFILD describes the ratio of the minimum to maximum soil permeability throughout the modeled area. Standard SWM practice does not adjust INFILD from its default value (USEPA, 2000).

Infiltration also depends on soil saturation. The nominal lower zone storage capacity (LZSN) describes the capacity of the deep subsurface area to retain moisture (described below). Lower LZSN increases soil saturation and decreases infiltration. The exponent in the infiltration equation (INFEXP) affects how infiltration changes as soil

saturation changes. Altering this behavior can greatly affect model predictions, but INFEXP is rarely changed from its default value (USEPA, 2000).

Runoff

Some water in surface detention storage runs off (suro) to an adjacent downslope land segment or to the stream. Many runoff simulation methods use the continuity and momentum equations, but these partial differential equations cannot be solved exactly (Wanielista et al., 1997). SWM approximates them through empirical modifications to the Chezy-Manning equation (Bicknell et al., 2001). This equation relates runoff velocity to an overland roughness coefficient (Manning's N), the depth of overland flow, and the energy gradient slope (Wanielista et al., 1997). SWM calculates the depth of overland flow by comparing the rate of precipitation supply with simulated levels of interception, infiltration, and upper zone storage (Bicknell et al., 2001).

VenSWM contains parameters that represent the terms in the Chezy-Manning equation. Manning's N (NSUR) describes the roughness of the land surface. Forested areas with heavy surface debris and areas with heavy turf have higher NSUR values than smooth areas like parking lots. Higher NSUR slows the flow of runoff, which delays peak discharge during a storm event. Higher NSUR also decreases runoff volume by increasing the amount of time that runoff is available for infiltration. The length (LSUR) and slope (SLSUR) of the overland flow plane determine the energy gradient slope. Steep slopes and short flow planes increase runoff velocity, causing runoff to reach the stream more quickly. They also increase runoff volume by reducing the time that the runoff is subject to infiltration.

Upper Zone Storage

In pervious land segments, some water in surface detention storage enters upper zone storage (uzi). Upper zone storage does not have a precise physical definition, but generally represents the area just under the soil surface. Vegetation, topography, and nominal lower zone storage capacity (LZSN) affect UZSN, the nominal upper zone storage capacity. Areas with heavy vegetation, low gradients, and high LZSN have

higher UZSN (USEPA, 2000). UZSN plays an important role in apportioning water between overland flow and subsurface processes, but has little effect on the annual water budget (USEPA, 2000).

Water enters upper zone storage only from surface detention storage. The amount of water that enters upper zone storage is primarily a function of the simulated upper zone saturation, which is dependent on the upper zone storage capacity (UZSN). Water leaves upper zone storage through evaporation (uzet) or by percolation (perc) to lower zone storage or active groundwater storage. Percolation depends on the permeability of the soil (INFILT) and upper zone saturation. More permeable soils and higher upper zone saturation increase percolation. Higher percolation decreases the volume of water that remains on the soil surface and is available for runoff.

Interflow Storage

Water from surface detention storage that does not infiltrate, run off, or move to upper zone storage moves to interflow storage. This representation of interflow is only a quasi-physical process because interflow storage is not available for infiltration or evaporation. Interflow storage represents subsurface flows (ifwo) to an adjacent downslope land segment or to the stream. Interflow outflow has an important effect on the shape of storm hydrographs. A high volume of interflow storage removes water from surface runoff and delays peak discharge during a storm event (USEPA, 2000).

Water enters interflow storage either from surface detention storage (ifwi) or from the interflow outflow of an adjacent land segment (ifwli). Water leaves interflow storage by flowing to an adjacent land segment or to the stream. Two parameters regulate interflow inflow and outflow. The interflow inflow parameter (INTFW) helps determine the volume of surface detention storage that moves to interflow storage instead of its alternative fates. The interflow recession coefficient (IRC) determines how quickly water leaves interflow storage, describing how the volume of interflow outflow changes from one time step to the next. Neither INTFW nor IRC have a direct physical meaning. Slope is the most prominent determinant of IRC (USEPA, 2000), but even this is not a direct physical relationship. The lack of a direct basis in the natural system is illustrated

by the fact that HSPF allows IRC to be a constant or a monthly value. Slope obviously does not change throughout the year. INTFW and IRC do not directly represent physical processes, but they allow the use of empirical data in the modeled watershed to help characterize unmeasurable processes that dictate how the watershed responds to storm events.

Lower Zone Storage

Water that infiltrates from surface detention storage (infil) or that percolates from upper zone storage (perc) goes to either lower zone storage (lzi) or to active groundwater storage (agwi). Lower zone storage represents the area beneath upper zone storage, including the root zone. It is an important determinant of the annual water budget because it is a primary supply for evapotranspiration, which removes a large amount of water from the system.

The rate at which water enters lower zone storage depends on the saturation of the three subsurface storages (upper zone, lower zone, and active groundwater). Water enters more slowly when lower zone storage is more saturated, but more quickly when the other storages are more saturated. Water leaves lower zone storage only through evapotranspiration. The nominal lower zone storage capacity (LZSN) regulates the saturation of the lower zone. LZSN depends on soil characteristics and precipitation levels (USEPA, 2000). Areas with higher precipitation have higher LZSN.

Active Groundwater Storage

Infiltrated and percolated water that does not enter lower zone storage enters active groundwater storage (agwi) or inactive groundwater (igwi). Active groundwater storage represents water storage in the water table and provides baseflow to the stream. Inactive groundwater (igwi) represents deep aquifers. Water that enters this storage leaves the system.

Water enters active groundwater storage from surface detention storage or upper zone storage. The saturation level of the three subsurface zones determines the volume that enters. The rate of entry is directly related to the saturation of the upper and lower

zones and inversely related to the saturation of active groundwater storage. Water may also enter active groundwater storage from the groundwater of an adjacent land segment (agwli). Water leaves groundwater through evapotranspiration (aget) or as active groundwater outflow (agwo) to the stream or to the groundwater of an adjacent land segment. The rate of groundwater outflow depends on the cross-sectional area of the water table and the energy gradient of groundwater flow (Bicknell et al., 2001). The amount of water in active groundwater storage determines both the cross-sectional area and the energy gradient.

Several parameters regulate groundwater behavior. DEEPFR represents the fraction of groundwater inflow from infiltration or percolation (igwi) that enters deep reservoirs and leaves the system. DEEPFR is frequently higher in high elevations (USEPA, 2000). The groundwater recession coefficient (AGWRC) describes how groundwater outflow changes over time. Complicated interactions among climate, topography, soils, and land use affect its value (USEPA, 2000). KVARY is a second groundwater recession. It allows nonlinear recession over time, which is useful when groundwater recession shows seasonal patterns (USEPA, 2000).

Evapotranspiration

Evapotranspiration removes water from five storages on or beneath the land surface. Adequate simulation of evapotranspiration is essential to achieve accurate hydrologic predictions because in most watersheds the volume of water leaving the watershed through evapotranspiration is actually greater than streamflow volume (Bicknell et al., 2001). VenSWM calculates the volume of evapotranspiration from a time series input of potential evapotranspiration and the simulated volume of water in each storage level. The algorithm draws from the storage zones sequentially. It first attempts to completely draw down baseflow. If additional potential evapotranspiration remains, it draws from interception storage. If it has still not filled the potential, it draws from the three lower levels.

Several parameters determine the amount of evapotranspiration from the three lower zones. BASETP specifies the fraction of baseflow that is subject to

evapotranspiration. Evapotranspiration from baseflow represents water drawn directly from baseflow by streamside vegetation (USEPA, 2000). AGWETP is the fraction of potential evapotranspiration (after removal from baseflow and interception storage) that can be obtained from active groundwater storage. Groundwater evapotranspiration simulates swampy areas in which the water table lies at the soil surface (USEPA, 2000). LZETP is an index that defines the amount of potential evapotranspiration to draw from lower zone storage. LZETP represents transpiration by vegetation and depends on vegetation type, density, root depth, and the amount of moisture in the soil (USEPA, 2000). Unlike the other evapotranspiration parameters, LZETP can be a monthly value to simulate the seasonal variation in plant activity.

Appendix B Benchmarking VenSWM with LSPC

To test the fidelity of VenSWM to LSPC, I compared the predictions produced by the two models for several analogous Emory River calibrations. I calibrated VenSWM models of the Emory River with several evaluation criteria and weather inputs. I then entered the calibrated parameters and weather inputs into LSPC. The output from the models generally corresponds very well. Linear regressions between the models' outputs produce slopes that are very close to 1.0 and coefficients of determination range from 0.94 to 0.998. If the models were perfect matches, the slope and coefficient of determination would both be 1.0. The slight deviations arise because of differences in programmer's art and the fact that VenSWM does not include an impervious component, lumps the land uses, and does not explicitly represent the stream network.

Figure B.1 shows a representative comparison of model output.[34] The models seem to be close matches. The slope in the figure is very close to 1.0 and the R^2 is more than 0.96. Visual inspection of the figure suggests that there is an influential outlier over 2,000 m^3/s (point A), but removing it from consideration does not reduce the R^2.

The models nevertheless show a few notable differences on a daily basis. Analysis of the deviations suggests that when the models use the parameters estimated by VenSWM, VenSWM is generally more accurate in predicting measured discharge. A good illustration of this is point B on Figure B.1. VenSWM simulated discharge of 410 m^3/s and LSPC simulated discharge of 741 m^3/s. The measured discharge on that date was only 272 m^3/s. Both models significantly overpredict flow, but VenSWM is much closer. Figure B.2 shows the hydrograph for this storm event. The yellow line is the measured values, the blue line is the VenSWM predictions, and the pink line is the LSPC predictions. There is an obvious difference between the models' predictions, and VenSWM reproduces measured flow more closely. LSPC seems to be "flashier" than VenSWM, predicting a rapid peak and recession in stream flow. Such a difference in behavior is likely due to the fact that VenSWM does not contain an impervious

[34] This particular output came from an Emory River calibration using the daily evaluation criterion and the composite weather input.

component. LSPC routes some water to the stream soon after the storm begins, but VenSWM slows that water in subsurface processes.

Other large differences between model predictions are more difficult to assess. The largest difference in total volume shown in Figure B.1 is point C. VenSWM simulated discharge of 1,465 m^3/s and LSPC simulated 970 m^3/s. Both models were inaccurate; the measured mean discharge on that date was 1,249 m^3/s. Figure B.3 shows the hydrograph for this storm. The yellow line is the measured values, the blue line is the VenSWM predictions, and the pink line is the LSPC predictions. It is difficult to determine which model more closely matches the data, but there is again an obvious difference between them. It is also difficult to hypothesize reasons for the differences in the predicted flow pattern.

Despite differences such as these, LSPC and VenSWM generally produce very similar predictions. When there are differences, it is not obvious that LSPC's simulations are more appropriate than VenSWM's, and VenSWM often give a better match with the observations. A thorough check of VenSWM did not reveal any programming differences from the HSPF source code. LSPC is currently available only in a beta version that has not been exhaustively tested (Wang, 2002b), so it may contain programming bugs that affect its predictions.[35] Based on these facts, I concluded that VenSWM is a faithful representation of SWM.

[35] My experience calibrating LSPC by hand revealed many bugs in functionality, if not necessarily in the prediction algorithms.

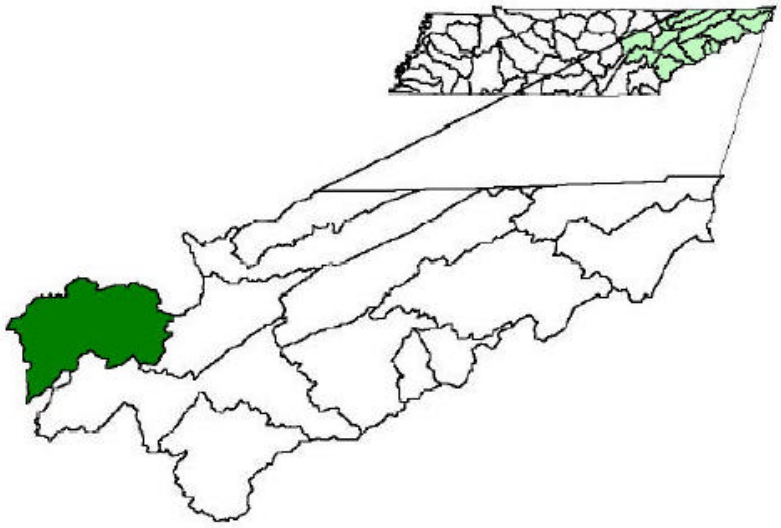


Figure 2.1. Location of the Emory River watershed

Source: TDEC. 2000a. Emory River Watershed (06010208) of the Tennessee River Basin: Water Quality Management Plan. Division of Water Pollution Control, Nashville.

Note: Each polygon represents a watershed delineated at the eight-digit hydrologic unit code level.

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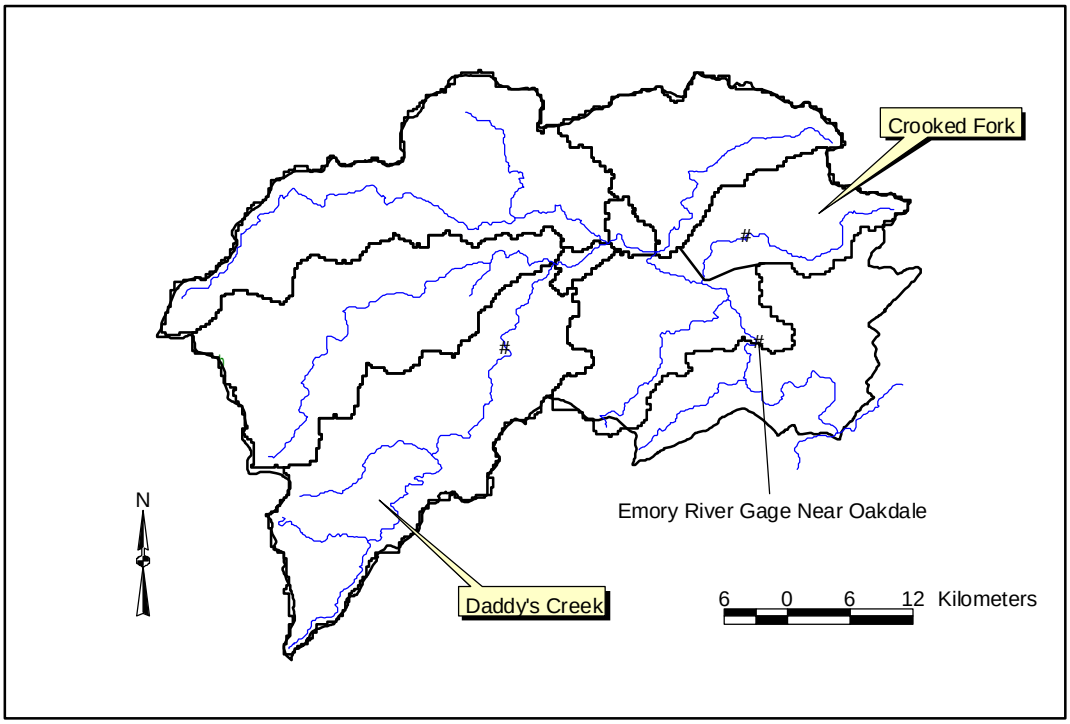
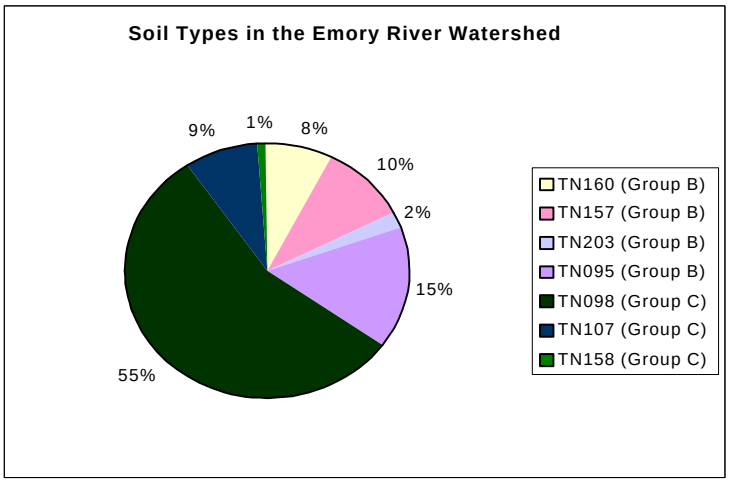
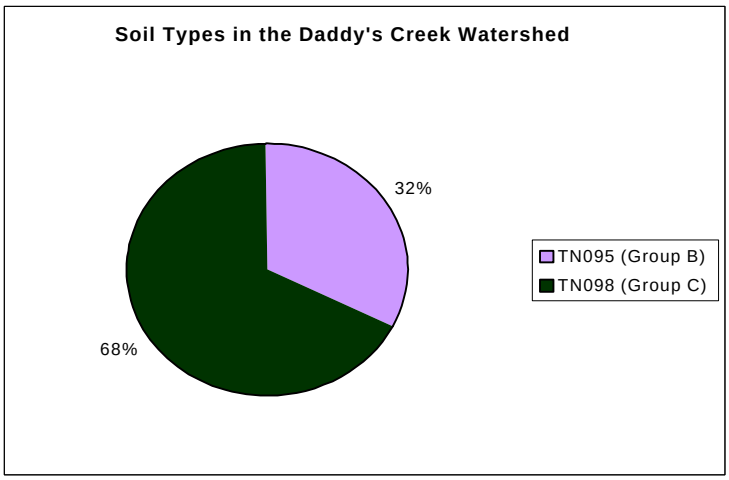


Figure 2.2. Locations of subwatersheds and stream gages

Source: Map by author

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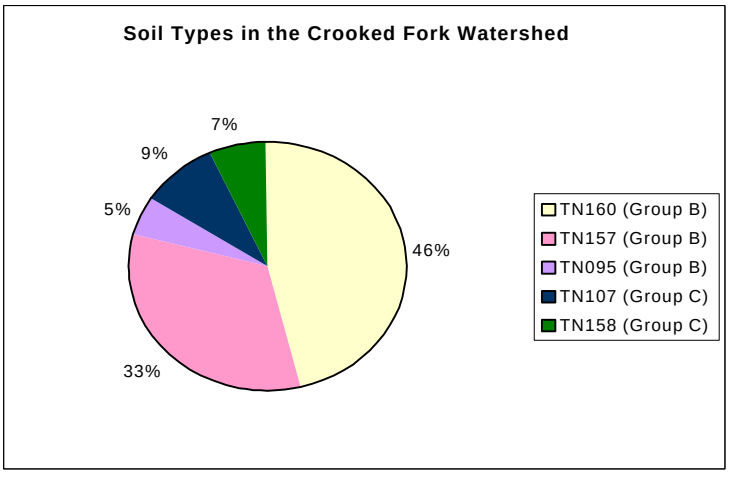


Figure 2.3. Hydrologic soil groups in the Emory River watershed

Source: TDEC. 2000a. Emory River Watershed (06010208) of the Tennessee River Basin: Water Quality Management Plan. Division of Water Pollution Control, Nashville.

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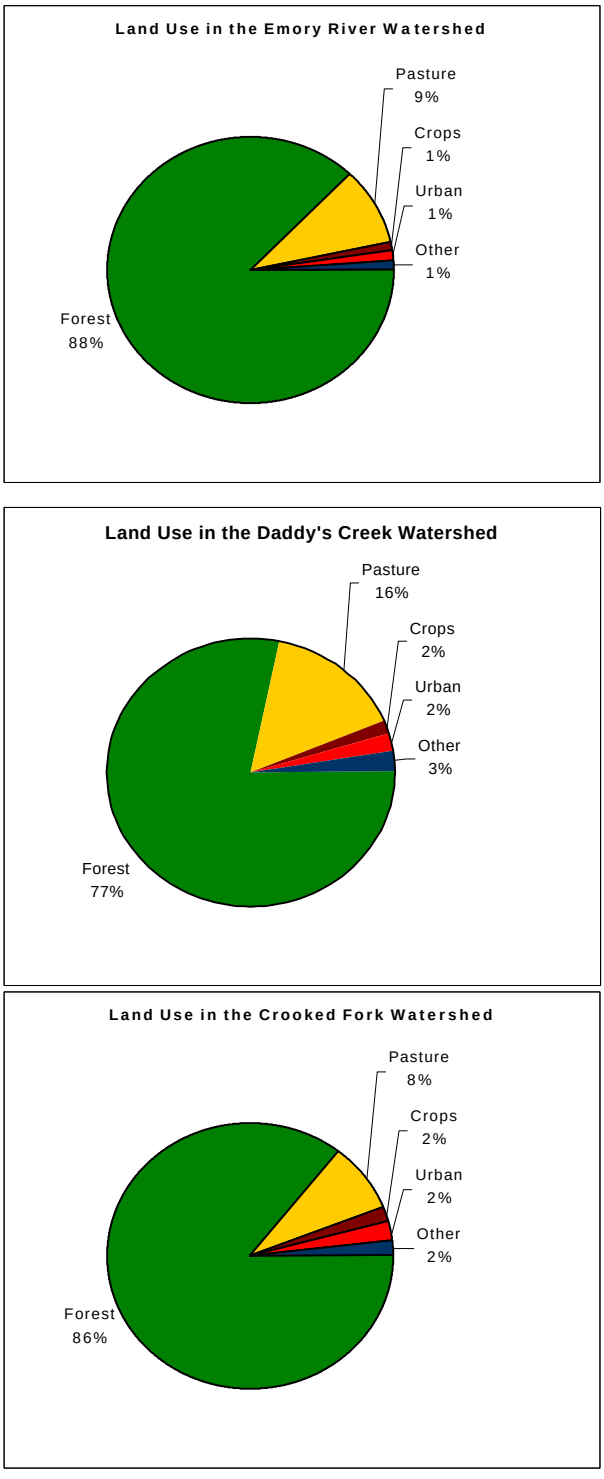


Figure 2.4. Land uses in the Emory River watershed

Source: TDEC. 2000a. Emory River Watershed (06010208) of the Tennessee River Basin: Water Quality Management Plan. Division of Water Pollution Control, Nashville.

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Figure 2.5. View of urbanized area in the Crooked Fork watershed

Source: Photo by author

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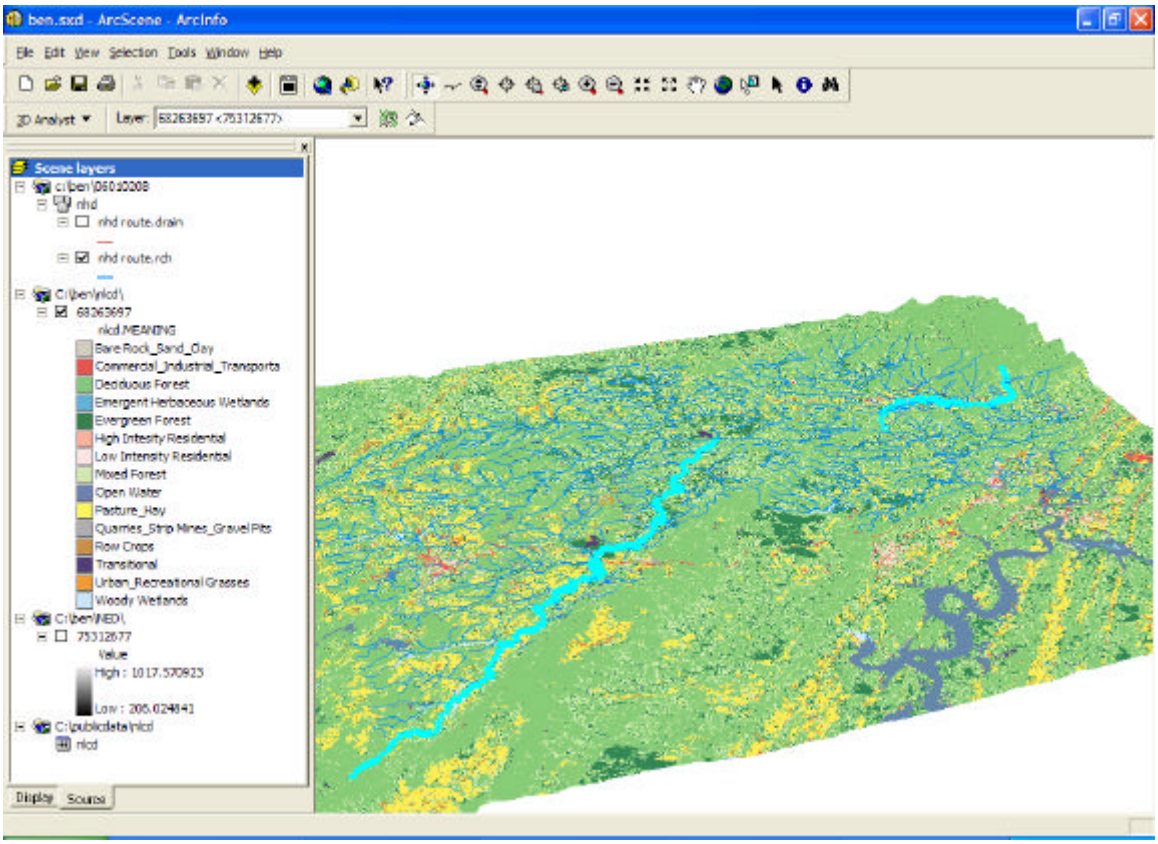


Figure 2.6. Topography in the Emory River watershed

Source: Map by Dr. Bruce Ralston

Note: Daddy's Creek is the highlighted stream in the lower left of the figure and Crooked Fork is the highlighted stream in the upper right of the figure.

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Figure 2.7. View of topography in the Crooked Fork watershed

Source: Photo by author

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Figure 2.8. View of topography in the Daddy's Creek watershed

Source: Photo by author

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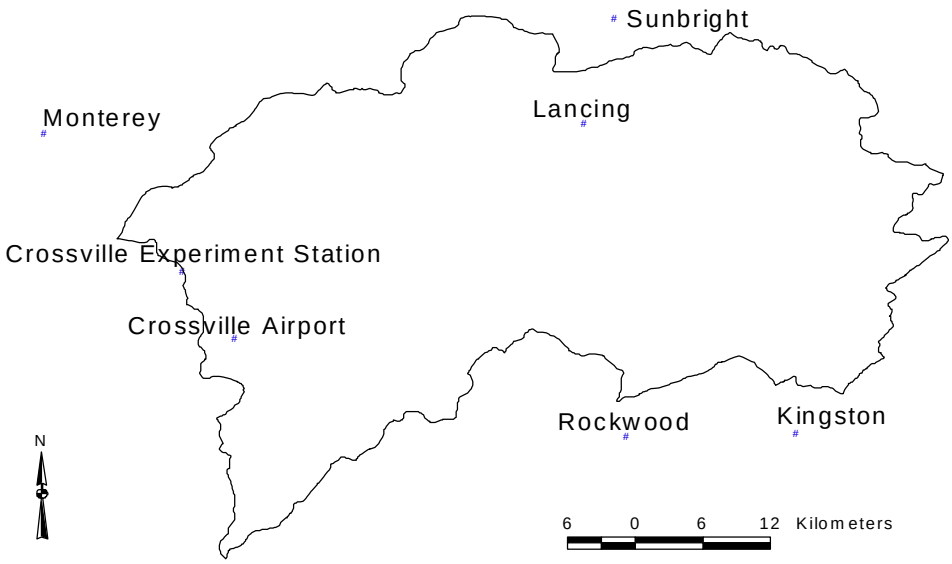


Figure 2.9. Weather stations near the Emory River watershed

Source: Map by author

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Table 2.1. Total Annual precipitation around the Emory River watershed

Year	Kingston	Knoxville	Lancing	Monterey	Crossville Experiment Station	Crossville Airport
1980	103	103	#N/A	117	114	109
1981	111	111	#N/A	144	133	134
1982	141	139	#N/A	174	162	166
1983	113	108	#N/A	157	153	135
1984	#N/A	123	#N/A	167	173	163
1985	89	92	#N/A	107	118	121
1986	98	82	#N/A	127	131	123
1987	83	88	#N/A	111	108	120
1988	103	88	#N/A	130	137	130
1989	174	143	#N/A	187	185	168
1990	155	140	156	161	166	135
1991	148	148	156	155	178	148
1992	126	112	135	143	153	133
1993	121	115	118	133	128	105
1994	167	161	153	168	177	175
1995	#N/A	109	128	150	151	157
1996	#N/A	125	161	174	160	160
1997	147	139	130	144	152	138
1998	#N/A	144	163	190	180	172
Annual Average	125	120	145	149	150	142

Source: NOAA. National Oceanic and Atmospheric Administration. 2002.

National Climatic Data Center. http://www.ncdc.noaa.gov/oa/climate/stationlocator.html.

Note: All data are in cm. Sunbright is not included because it has a large amount of missing data, which prevents calculation of its annual totals. Kingston also lacks a great deal of data in several years. Lancing did not begin to record data until 1989, and its first complete year is 1990.

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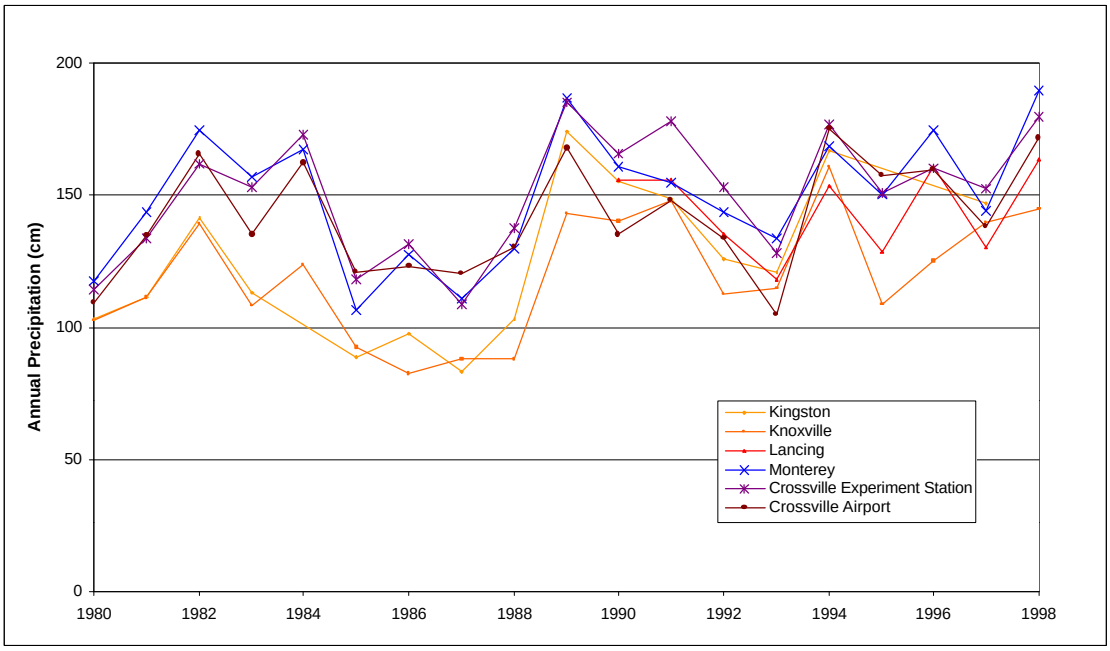


Figure 2.10. Variability of precipitation around the Emory River watershed

Source: NOAA. National Oceanic and Atmospheric Administration. 2002. National Climatic Data Center. http://www.ncdc.noaa.gov/oa/climate/stationlocator.html.

Note: Red lines represent stations to the east and blue lines represent stations to the west.

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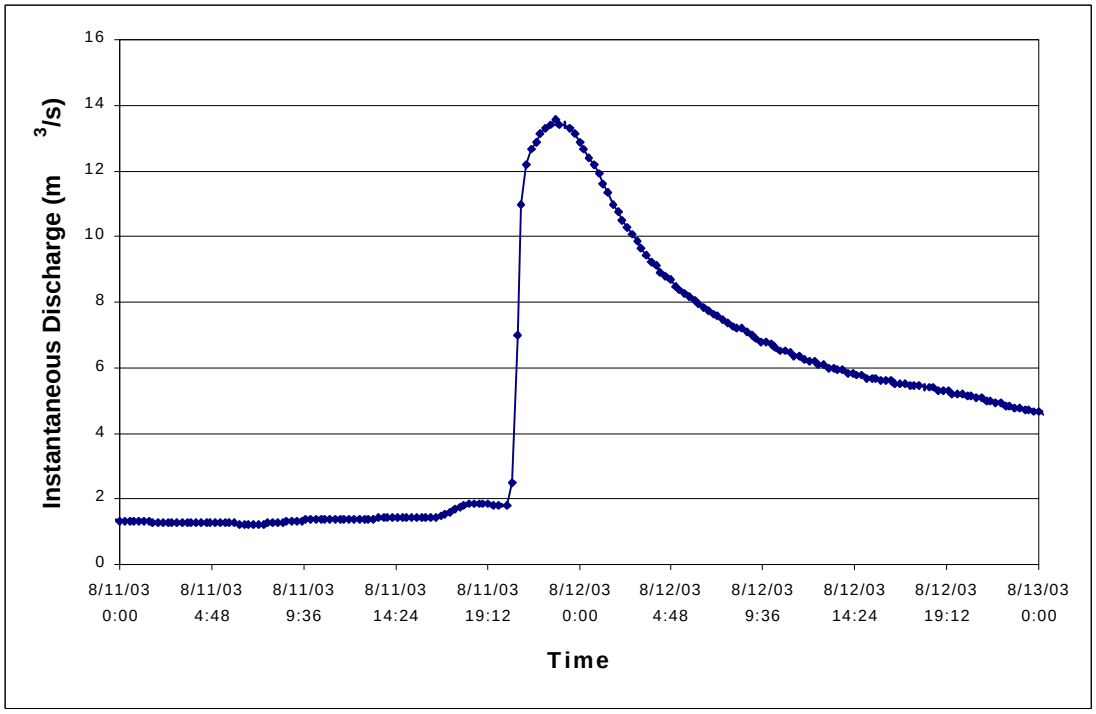


Figure 4.1. Daddy's Creek Discharge, 8/11/03 – 8/13/03

Source: USGS. 2003a. NWIS Site Information For Tennessee.

http://waterdata.usgs.gov/tn/nwis/uv/?site_no=03539600.

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Table 4.1. TMDL error targets

Metric	Fractional Error
Fall	0.30
Winter	0.30
Spring	0.30
Summer	0.30
10% Highest Flows	0.15
50% Lowest Flows	0.10

Source: TDEC. 2000b. Total Maximum Daily Load for Fecal Coliform in Sinking Creek: Watauga River Watershed, Tennessee (HUC 06010103). Division of Water Pollution Control, Nashville.

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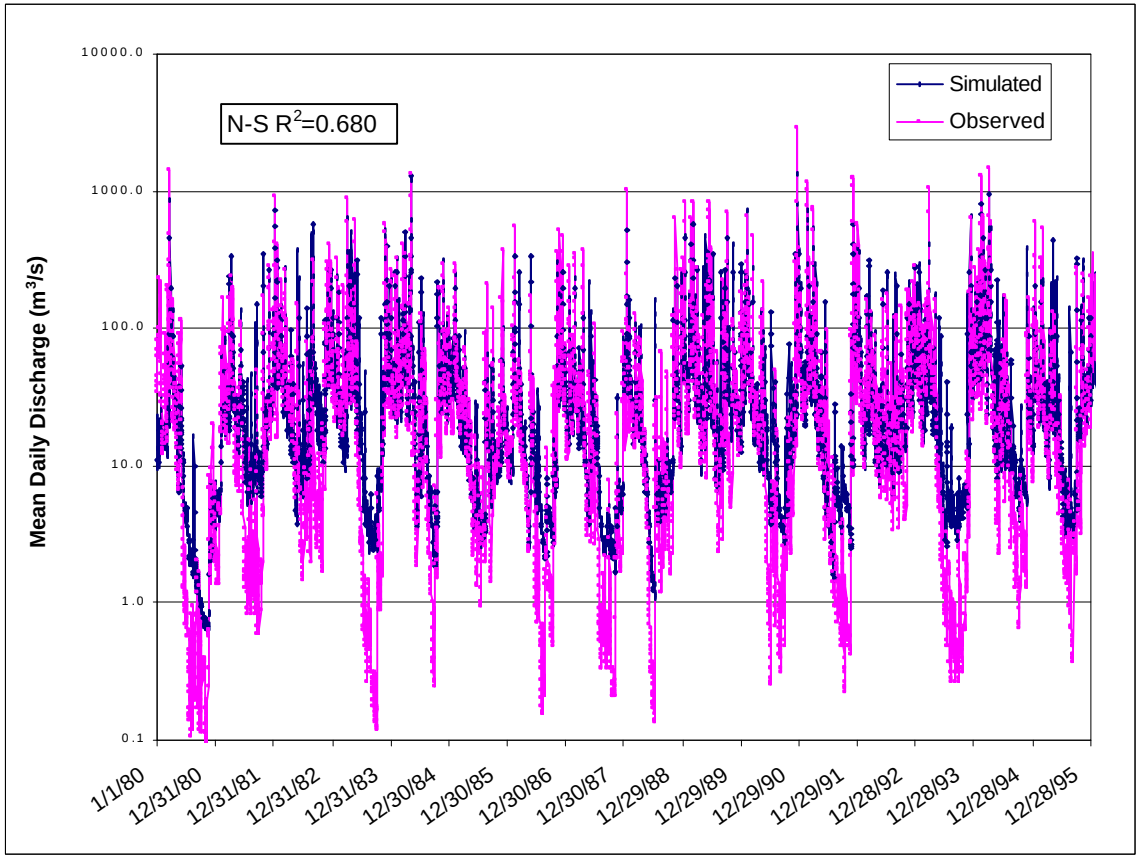


Figure 5.1. Calibration (1a) – Simulated and observed discharge at Oakdale gage during calibration period

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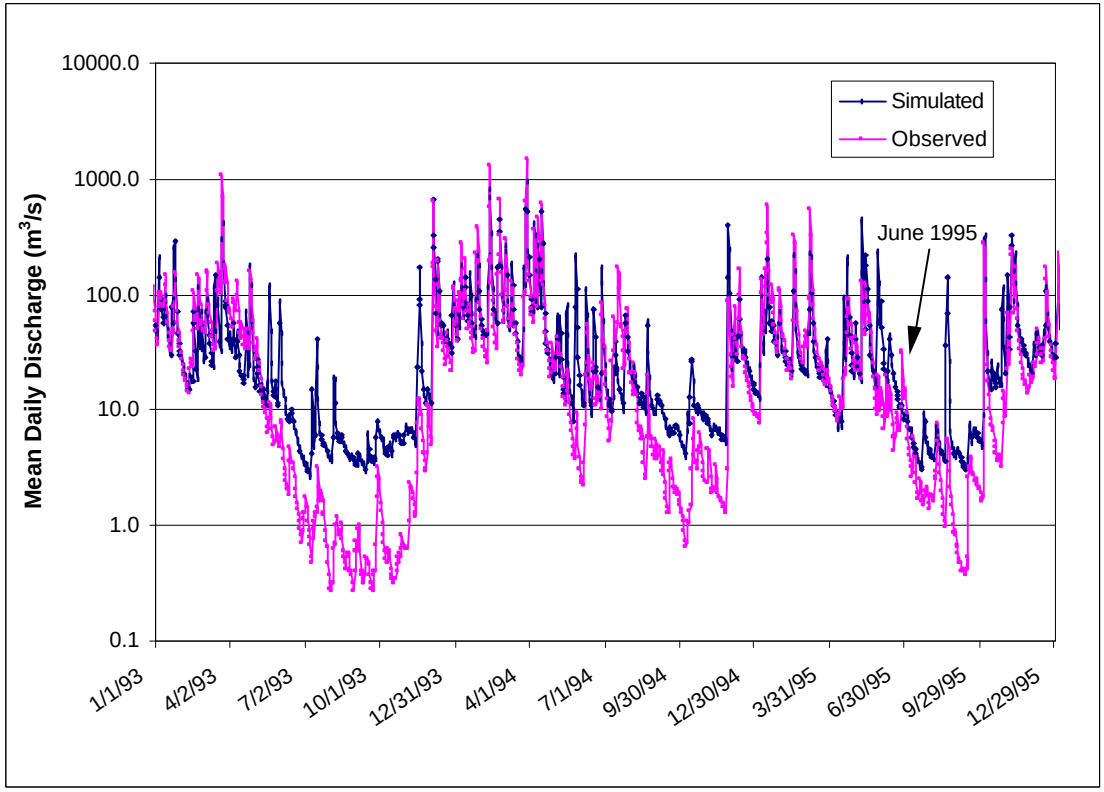


Figure 5.2. Calibration (1a) – Simulated and observed discharge at Oakdale gage during last three years of calibration

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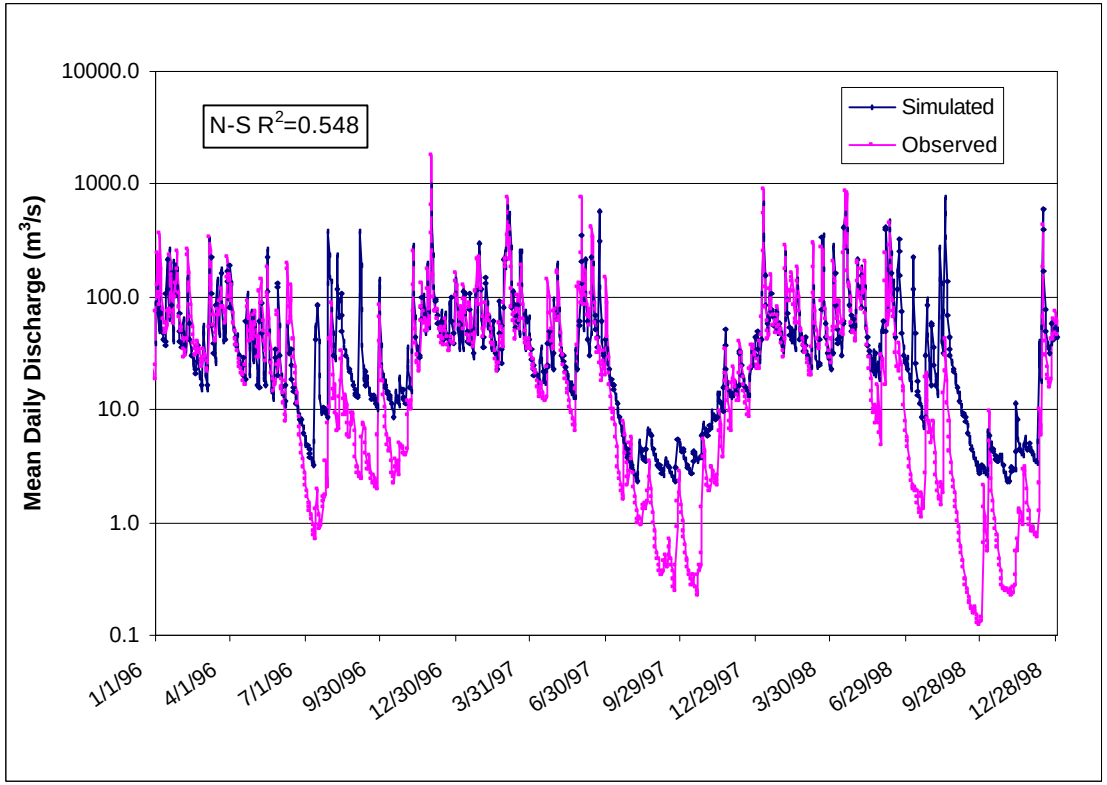


Figure 5.3. Calibration (1a) – Simulated and observed discharge at Oakdale gage during validation period

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Table 5.1. Daily Nash-Sutcliffe R^2 accuracy from HSPF and NPSM Studies

Study	Calibration	Validation
Laroche et al. (1996)	0.51	0.12
Srinivasan et al. (1998)	0.55	0.57
Carrubba (2000)	0.45	0.31
Carrubba (2000)	0.31	0.31
Carrubba (2000)	-0.66	0.37
Englemann et al. (2002)	0.67	0.50
This Study: Emory River	0.68	0.55

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Table 5.2. Calibration (1a) – Annual fractional errors in predicted total volume at the Oakdale gage

Metric	Mean Calibration Error	Median Calibration Error	Mean Validation Error	Median Validation Error
Fall	0.26	0.25	**0.34**	**0.34**
Winter	0.16	0.13	0.14	0.14
Spring	0.18	0.14	0.12	0.15
Summer	**1.92**	**1.29**	**5.23**	**4.32**
10% Highest Flows	**0.23**	**0.22**	0.14	0.08
50% Lowest Flows	**1.70**	**1.45**	**2.66**	**1.87**

Note: Bold numerals indicate errors that exceed the TDEC targets.

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Table 5.3. Calibration (1a) – Parameter values

Parameter	Description	Function Of	Comments	Typical Min	Typical Max	Possible Min	Possible Max	Calibration (1a)
LZSN	Lower zone nominal soil moisture storage	Soils, climate		3	8	2	15	11.5
INFILT	Index to infiltration capacity of the soil	Soils, land use	Divides surface/subsurface flow	0.01	0.25	0.001	0.5	0.092
LSUR	Length of overland flow plane	Topography	Estimate from maps or GIS	200	500	100	700	534
SLSUR	Slope of overland flow plane	Topography	Estimate from maps or GIS	0.01	0.15	0.001	0.3	0.07
KVARY	Groundwater recession flow parameter	Baseflow recession	If recession varies with grndwtr levels	0	3	0	5	1.67
AGWRC	Basic groundwater recession rate	Baseflow recession		0.92	0.99	0.85	0.999	0.99
INFEXP	Exponent in infiltration equation	Soils variability	Usually default to 2	2	2	1	3	3
INFILD	Ratio of max to min infiltration capacity	Soils variability	Usually default to 2	2	2	1	3	2
DEEPFR	Frac groundwater inflow to deep recharge	Geology, grndwtr recharge		0	0.2	0	0.5	0
BASETP	Frac remaining ET from baseflow	Riparian vegetation	Direct ET from riparian vegetation	0	0.05	0	0.2	0.04
AGWETP	Frac remaining ET from active grndwtr strg	Marsh/wetlands extent	Direct ET from shallow groundwater	0	0.05	0	0.2	0.01
UZSN	Upper zone nominal soil moisture strg	Soil conditions, land use	Accounts for near-surface retention	0.1	1	0.05	2	0.22
NSUR	Manning's n for overland flow	Surface conditions, land use		0.15	0.35	0.1	0.5	0.5
INTFW	Interflow inflow parameter	Soils, topography, land use	Based on hydrograph separation	1	3	1	10	7.59
IRC	Interflow recession parameter	Soils, topography, land use		0.5	0.7	0.3	0.85	0.3
CEPSC	Interception storage	Veg type/density, land use	Monthly values used	0.03	0.2	0.01	0.4	
CEPJAN								0.03
CEPFEB								0.03
CEPMAR								0.03
CEPAPR								0.08
CEPMAY								0.12
CEPJUN								0.12
CEPJUL								0.12
CEPAUG								0.12
CEPSEP								0.12
CEPOCT								0.06
CEPNOV								0.03
CEPDEC								0.03
LZETP	Lower zone evapotranspiration parameter	Veg type/density, root depth	Monthly values used	0.2	0.7	0.1	0.9	
LZEJAN								0.11
LZEFEB								0.11
LZEMAR								0.11
LZEAPR								0.33
LZEMAY								0.78
LZEJUN								0.78
LZEJUL								0.89
LZEAUG								0.89
LZESEP								0.89
LZEOCT								0.67
LZENOV								0.22
LZEDEC								0.22

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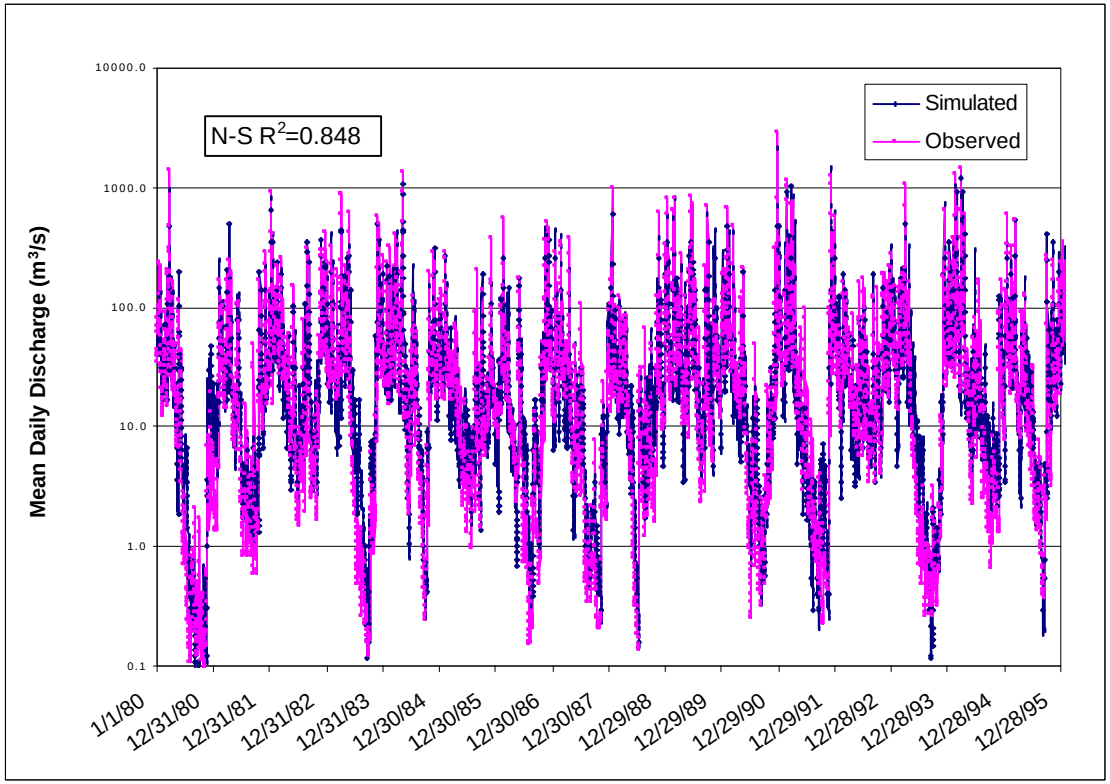


Figure 5.4. Calibration (1b) – Simulated and observed discharge at Oakdale gage during calibration period

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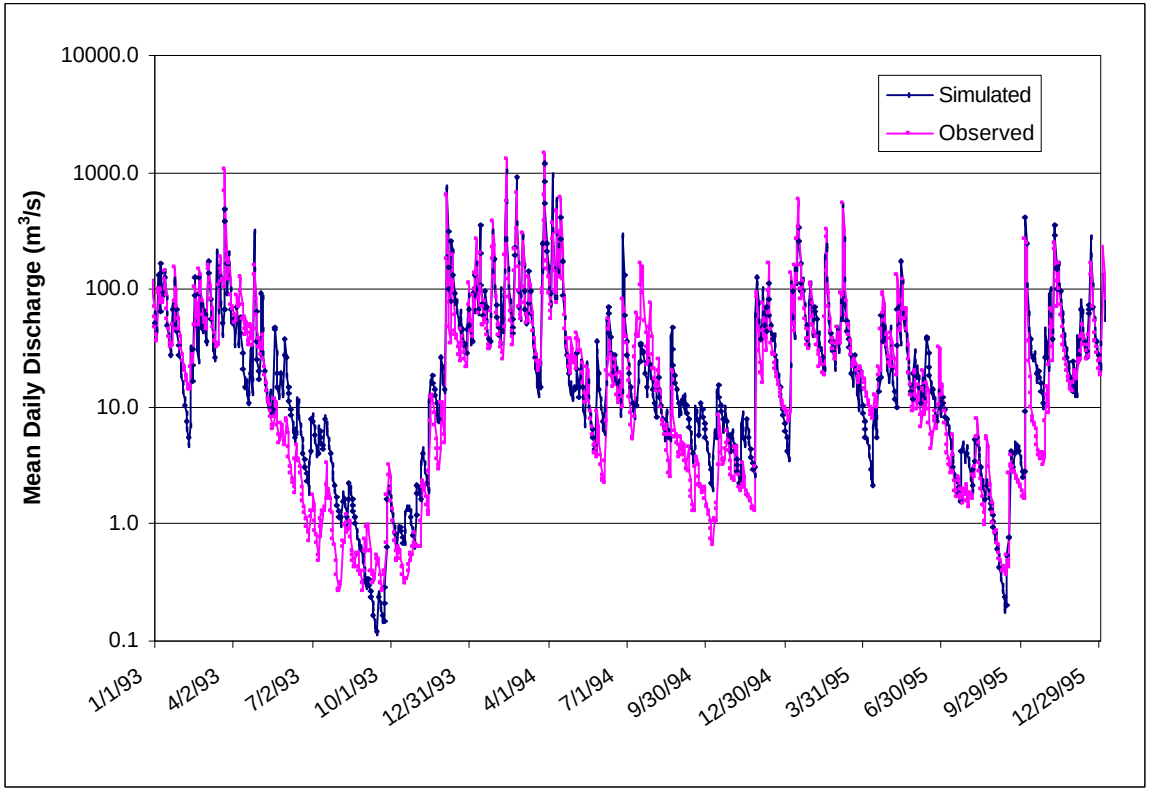


Figure 5.5. Calibration (1b) – Simulated and observed discharge at Oakdale gage during last three years of calibration

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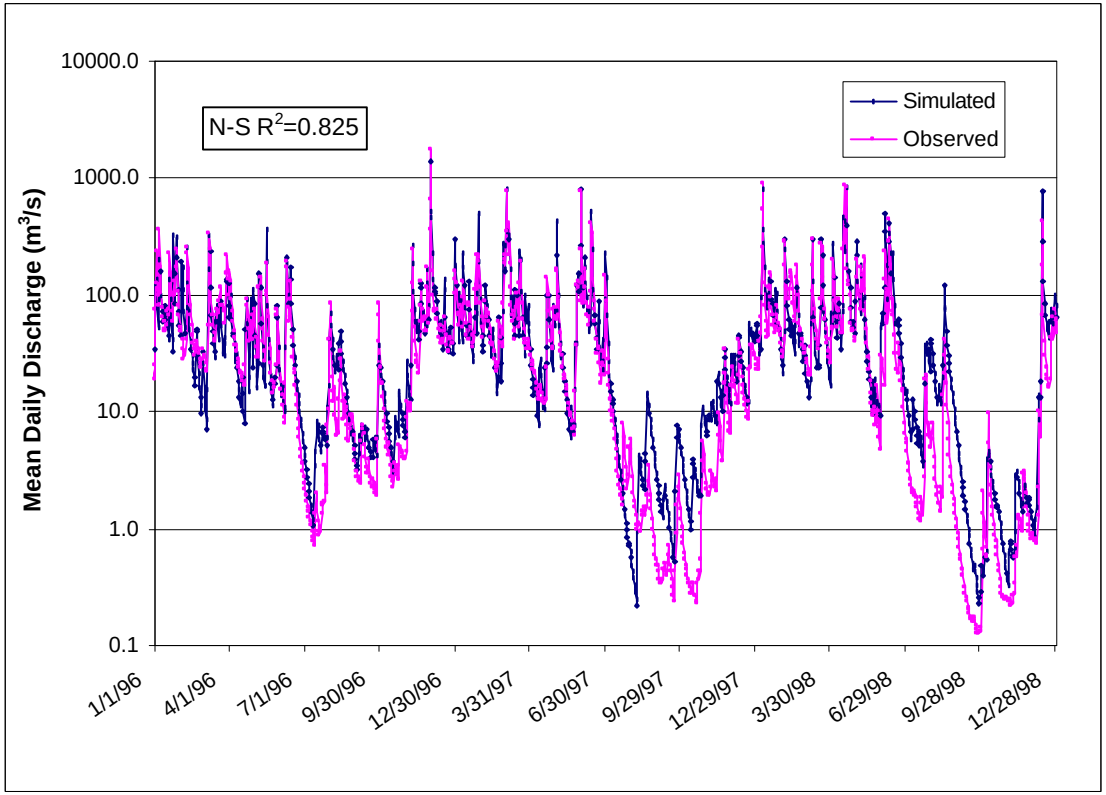


Figure 5.6. Calibration (1b) – Simulated and observed discharge at Oakdale gage during validation period

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Table 5.4. Calibration (1b) – Parameter values

Parameter	Description	Function Of	Comments	Typical Min	Typical Max	Possible Min	Possible Max	White Oak Creek	Sinking Creek	Calibration (1b)	ER Daily Monty Only
LZSN	Lower zone nominal soil moisture storage	Soils, climate		3	8	2	15	7	5	3.8	11.5
INFILT	Index to infiltration capacity of the soil	Soils, land use	Divides surface/subsurface flow	0.01	0.25	0.001	0.5	0.08	0.05	0.066	0.092
LSUR	Length of overland flow plane	Topography	Estimate from maps or GIS	200	500	100	700	1440	500	534	534
SLSUR	Slope of overland flow plane	Topography	Estimate from maps or GIS	0.01	0.15	0.001	0.3	0.14	0.029-0.15	0.07	0.07
KVARY	Groundwater recession flow parameter	Baseflow recession	If recession varies w/ grndwtr lvls	0	3	0	5	0	0	0.18	1.67
AGWRC	Basic groundwater recession rate	Baseflow recession		0.92	0.99	0.85	0.999	0.99	0.98	0.89	0.99
INFEXP	Exponent in infiltration equation	Soils variability	Usually default to 2	2	2	1	3	2	2	2	3
INFILD	Ratio of max to min infiltration capacity	Soils variability	Usually default to 2	2	2	1	3	2	2	2	2
DEEPFR	Frac groundwater inflow to deep recharge	Geology, grndwtr recharge		0	0.2	0	0.5	0	0.35	0	0
BASETP	Frac remaining ET from baseflow	Riparian vegetation	Direct ET from riparian vegetation	0	0.05	0	0.2	0	0	0	0.04
AGWETP	Frac remaining ET from active grndwtr strg	Marsh/wetlands extent	Direct ET from shallow groundwater	0	0.05	0	0.2	0	0	0	0.01
UZSN	Upper zone nominal soil moisture strg	Soil conditions, land use	Accounts for near-surface retention	0.1	1	0.05	2	0.8	0.7	0.82	0.22
NSUR	Manning's n for overland flow	Surface conditions, land use		0.15	0.35	0.1	0.5	0.3	0.3	0.5	0.5
INTFW	Interflow inflow parameter	Soils, topography, land use	Based on hydrograph separation	1	3	1	10	4	5	1.51	7.59
IRC	Interflow recession parameter	Soils, topography, land use		0.5	0.7	0.3	0.85	0.3	0.5	0.3	0.3
CEPSC	Interception storage	Veg type/density, land use	Monthly values used	0.03	0.2	0.01	0.4				
CEPJAN								0.01	0.01	0.03	0.03
CEPFEB								0.01	0.01	0.03	0.03
CEPMAR								0.03	0.03	0.03	0.03
CEPAPR								0.08	0.08	0.08	0.08
CEPMAY								0.12	0.12	0.12	0.12
CEPJUN								0.12	0.12	0.12	0.12
CEPJUL								0.12	0.12	0.12	0.12
CEPAUG								0.12	0.12	0.12	0.12
CEPSEP								0.12	0.12	0.12	0.12
CEPOCT								0.06	0.06	0.06	0.06
CEPNOV								0.03	0.03	0.03	0.03
CEPDEC								0.01	0.01	0.03	0.03
LZETP	Lower zone evapotranspiration parameter	Veg type/density, root depth	Monthly values used	0.2	0.7	0.1	0.9				
LZEJAN								0.2	0.2	0.11	0.11
LZEFEB								0.2	0.2	0.11	0.11
LZEMAR								0.2	0.2	0.11	0.11
LZEAPR								0.3	0.3	0.33	0.33
LZEMAY								0.4	0.4	0.78	0.78
LZEJUN								0.4	0.4	0.78	0.78
LZEJUL								0.4	0.4	0.89	0.89
LZEAUG								0.3	0.3	0.89	0.89
LZESEP								0.3	0.3	0.89	0.89
LZEOCT								0.2	0.2	0.67	0.67
LZENOV								0.2	0.2	0.22	0.22
LZEDEC								0.2	0.2	0.22	0.22
Weather Stations											
Monterey Daily										0.35	
Monterey Hourly										0.46	
Lancing										0.87	
C'ville Apt v. Exp Station										0.75	
Kingston										0.24	
North-to-West										0.33	

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Table 5.5. Calibration (1b) – Annual fractional errors in predicted total discharge at the Oakdale gage

Calibration (1b)				
Metric	Mean Calibration Error	Median Calibration Error	Mean Validation Error	Median Validation Error
Fall	**0.36**	0.17	**0.52**	**0.68**
Winter	0.08	0.06	0.10	0.11
Spring	0.18	0.15	0.09	0.09
Summer	**0.74**	**0.37**	**1.20**	**0.56**
10% Highest Flows	0.12	0.12	0.10	0.11
50% Lowest Flows	**0.78**	**0.67**	**0.92**	**0.68**
From Calibration (1a)				
Metric	Mean Calibration Error	Median Calibration Error	Mean Validation Error	Median Validation Error
Fall	0.26	0.25	**0.34**	**0.34**
Winter	0.16	0.13	0.14	0.14
Spring	0.18	0.14	0.12	0.15
Summer	**1.92**	**1.29**	**5.23**	**4.32**
10% Highest Flows	**0.23**	**0.22**	0.14	0.08
50% Lowest Flows	**1.70**	**1.45**	**2.66**	**1.87**

Note: Bold numerals indicate errors that exceed the TDEC target.

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Table 5.6. Calibration (1b) – Annual fractional errors in highest flows at Oakdale gage

	10% Highest Flows		
	Mean Daily Discharge (m^3/s)		
	Simulated	Observed	Fractional Error
1980	159	185	-0.14
1981	115	125	-0.08
1982	214	237	-0.10
1983	201	257	**-0.22**
1984	248	263	-0.06
1985	94	118	**-0.21**
1986	150	161	-0.07
1987	114	135	-0.15
1988	131	152	-0.14
1989	279	340	**-0.18**
1990	259	304	-0.15
1991	395	359	0.10
1992	153	165	-0.08
1993	164	192	-0.15
1994	354	344	0.03
1995	178	189	-0.06
1996	210	246	-0.15
1997	238	214	0.11
1998	274	282	-0.03

Note: Bold numerals indicate errors that exceed the TDEC target.

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Table 5.7. Calibration (1b) – Annual fractional errors in summer and lowest flows at Oakdale gage

	Summer Flows				**50% Lowest Flows**		
	Mean Daily Discharge (m^3/s)				Mean Daily Discharge (m^3/s)		
	Simulated	Observed	Fractional Error		Simulated	Observed	Fractional Error
1980	1.2	0.5	**1.43**		2.6	0.7	**2.54**
1981	3.4	3.7	-0.10		6.5	3.8	**0.69**
1982	33.2	16.7	**0.98**		15.2	7.8	**0.97**
1983	3.7	0.8	**3.44**		7.9	4.0	**0.99**
1984	25.4	17.5	**0.45**		15.7	10.8	**0.45**
1985	9.3	12.3	-0.24		8.9	7.0	**0.28**
1986	4.6	1.8	**1.62**		6.3	3.5	**0.78**
1987	4.6	5.8	-0.21		3.8	1.9	**0.96**
1988	11.1	9.4	0.18		10.5	5.3	**0.96**
1989	33.6	33.2	0.01		22.9	15.7	**0.46**
1990	4.4	3.0	**0.48**		5.9	3.6	**0.65**
1991	1.8	3.1	**-0.43**		3.6	4.2	**-0.16**
1992	23.7	26.8	-0.12		12.8	13.2	-0.03
1993	2.2	0.8	**1.63**		4.0	1.5	**1.59**
1994	13.2	19.2	**-0.31**		11.1	7.0	**0.59**
1995	3.0	2.5	0.22		8.9	6.1	**0.44**
1996	12.3	8.7	**0.42**		14.1	10.6	**0.33**
1997	9.3	5.9	**0.56**		7.9	4.7	**0.68**
1998	14.2	3.9	**2.62**		9.1	3.3	**1.74**

Note: Bold numerals indicate errors that exceed the TDEC target.

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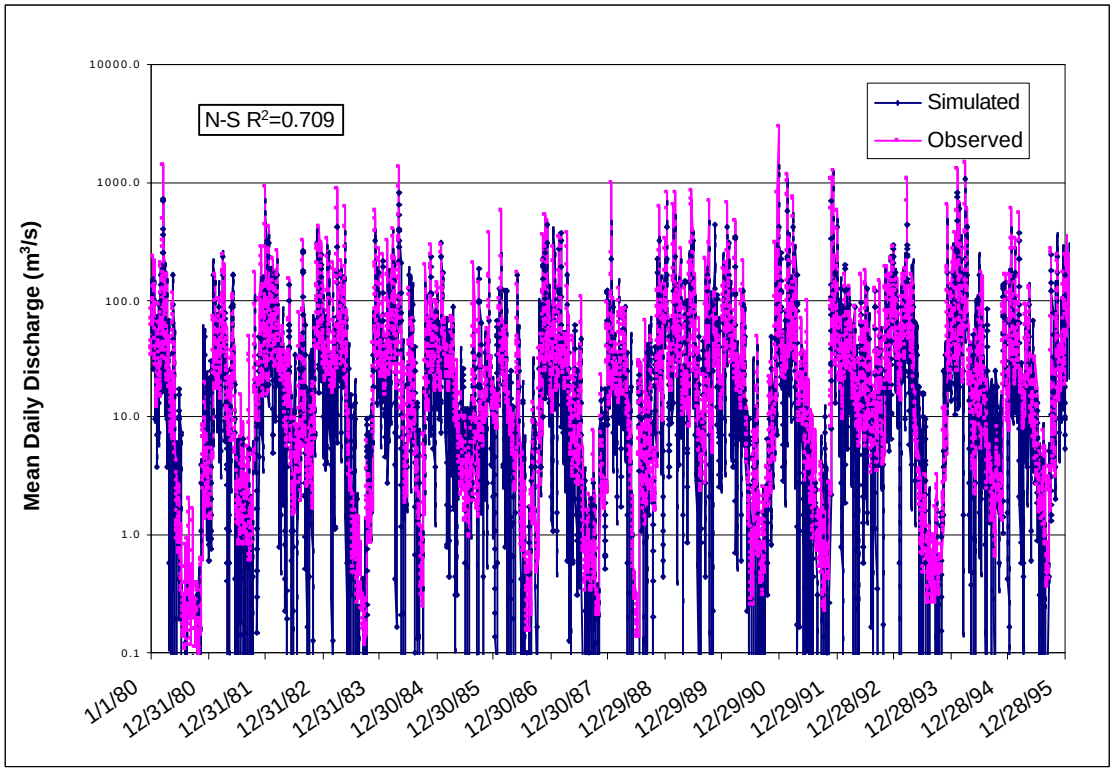


Figure 5.7. Calibration (1c) – Simulated and observed discharge at Oakdale gage during calibration period

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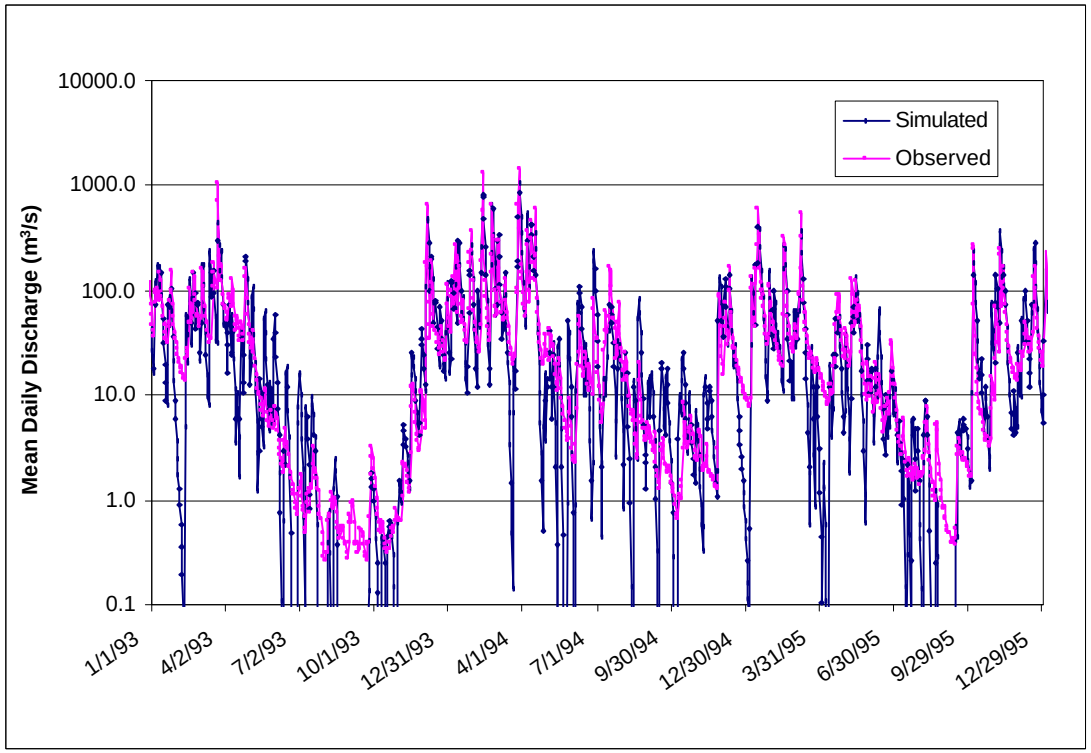


Figure 5.8. Calibration (1c) – Simulated and observed discharge at Oakdale gage during last three years of calibration

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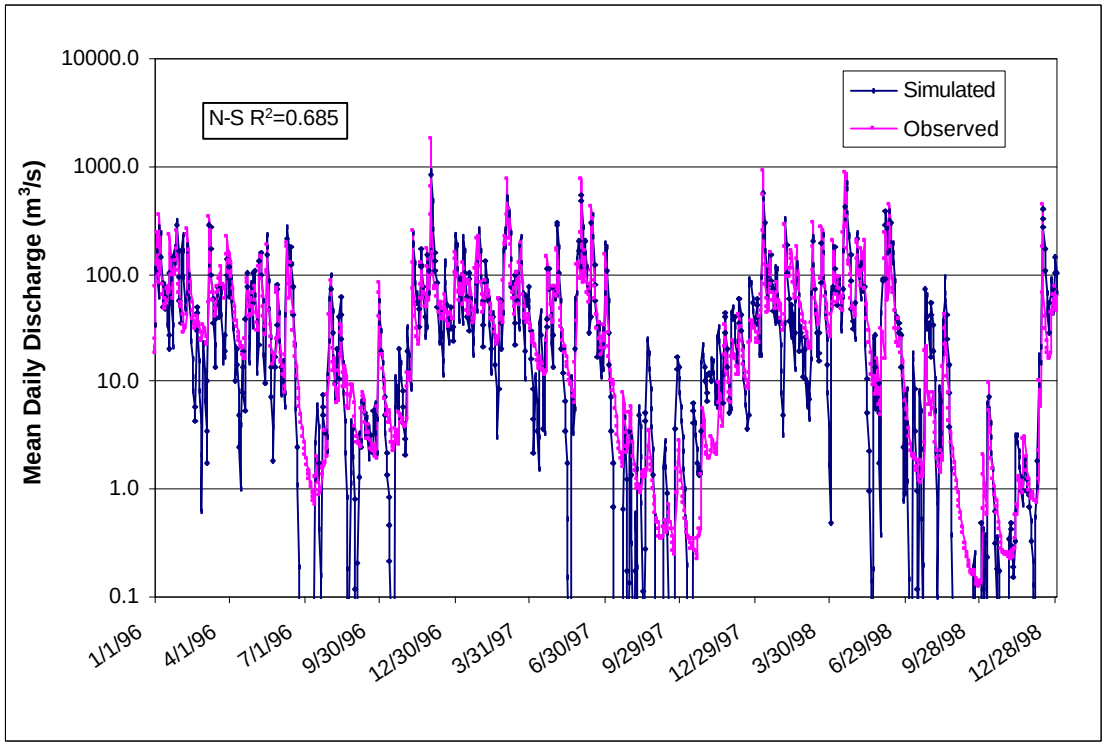


Figure 5.9. Calibration (1c) – Simulated and observed discharge at Oakdale gage during validation period

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Table 5.8. Annual fractional errors in Calibrations (1c) and (1b)

Calibration (1c) - Seasonal Criterion				
Metric	Mean Calibration Error	Median Calibration Error	Mean Validation Error	Median Validation Error
Fall	**0.35**	0.20	**0.60**	**0.74**
Winter	0.08	0.07	0.11	0.12
Spring	0.21	0.21	0.08	0.11
Summer	**0.47**	**0.36**	**0.75**	**0.50**
10% Highest Flows	0.10	0.11	0.12	0.12
50% Lowest Flows	**0.36**	**0.28**	**0.46**	**0.54**
Calibration (1b) - Daily Criterion				
Metric	Mean Calibration Error	Median Calibration Error	Mean Validation Error	Median Validation Error
Fall	**0.36**	0.17	**0.52**	**0.68**
Winter	0.08	0.06	0.10	0.11
Spring	0.18	0.15	0.09	0.09
Summer	**0.74**	**0.37**	**1.20**	**0.56**
10% Highest Flows	0.12	0.12	0.10	0.11
50% Lowest Flows	**0.78**	**0.67**	**0.92**	**0.68**

Note: Bold numerals indicate errors that exceed the TDEC target.

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Table 5.9. Calibration (1c) – Errors in each year of calibration and validation

	Summer Flows				**50% Lowest Flows**				**10% Highest Flows**		
	Mean Daily Discharge (m^3/s)				Mean Daily Discharge (m^3/s)				Mean Daily Discharge (m^3/s)		
	Simulated	Observed	Fractional Error		Simulated	Observed	Fractional Error		Simulated	Observed	Fractional Error
1980	0.6	0.5	0.15		2	1	**1.28**		169.2	185.3	-0.09
1981	1.2	3.7	**-0.67**		4	4	-0.06		105.7	125.4	**-0.16**
1982	23.8	16.8	**0.42**		10	8	**0.32**		219.3	237.1	-0.07
1983	2.0	0.9	**1.29**		5	4	**0.26**		203.5	256.8	**-0.21**
1984	27.2	17.5	**0.56**		12	11	**0.11**		232.2	263.1	-0.12
1985	9.0	12.3	-0.27		7	7	-0.02		102.1	118.3	-0.14
1986	4.3	1.8	**1.44**		5	4	**0.32**		152.0	161.2	-0.06
1987	4.1	5.9	**-0.30**		3	2	**0.31**		132.6	134.6	-0.01
1988	11.6	9.5	0.22		9	5	**0.64**		141.6	152.1	-0.07
1989	33.2	33.2	0.00		17	16	0.09		301.0	339.8	-0.11
1990	4.3	3.0	**0.42**		4	4	**0.26**		265.2	304.3	-0.13
1991	1.1	3.2	**-0.65**		3	4	**-0.27**		401.1	358.7	0.12
1992	23.5	27.0	-0.13		9	13	**-0.29**		171.2	164.9	0.04
1993	1.4	0.8	**0.70**		3	2	**0.93**		166.2	192.5	-0.14
1994	15.6	19.6	-0.20		10	7	**0.40**		378.2	344.5	0.10
1995	2.2	2.6	-0.16		7	6	**0.15**		197.6	189.1	0.04
1996	10.1	9.1	0.10		10	11	-0.06		217.2	246.4	-0.12
1997	8.9	5.9	**0.50**		7	5	**0.54**		248.8	214.4	**0.16**
1998	10.5	4.0	**1.65**		6	3	**0.77**		262.5	282.1	-0.07

Note: Bold numerals indicate errors that exceed the TDEC target.

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Table 5.10. Calibration (1c) – Parameter values

Parameter	Description	Function Of	Comments	Typical Min	Typical Max	Possible Min	Possible Max	Calibration (1b)	Calibration (1c)
LZSN	Lower zone nominal soil moisture storage	Soils, climate		3	8	2	15	3.8	3.5
INFILT	Index to infiltration capacity of the soil	Soils, land use	Divides surface/subsurface flow	0.01	0.25	0.001	0.5	0.066	0.079
LSUR	Length of overland flow plane	Topography	Estimate from maps or GIS	200	500	100	700	534	534
SLSUR	Slope of overland flow plane	Topography	Estimate from maps or GIS	0.01	0.15	0.001	0.3	0.07	0.07
KVARY	Groundwater recession flow parameter	Baseflow recession	If recession varies w/ grndwtr lvls	0	3	0	5	0.18	3
AGWRC	Basic groundwater recession rate	Baseflow recession		0.92	0.99	0.85	0.999	0.89	0.89
INFEXP	Exponent in infiltration equation	Soils variability	Usually default to 2	2	2	1	3	2	2
INFILD	Ratio of max to min infiltration capacity	Soils variability	Usually default to 2	2	2	1	3	2	2
DEEPFR	Frac groundwater inflow to deep recharge	Geology, grndwtr recharge		0	0.2	0	0.5	0	0
BASETP	Frac remaining ET from baseflow	Riparian vegetation	Direct ET from riparian vegetation	0	0.05	0	0.2	0	0
AGWETP	Frac remaining ET from active grndwtr strg	Marsh/wetlands extent	Direct ET from shallow groundwater	0	0.05	0	0.2	0	0.03
UZSN	Upper zone nominal soil moisture strg	Soil conditions, land use	Accounts for near-surface retention	0.1	1	0.05	2	0.82	1.00
NSUR	Manning's n for overland flow	Surface conditions, land use		0.15	0.35	0.1	0.5	0.5	0.5
INTFW	Interflow inflow parameter	Soils, topography, land use	Based on hydrograph separation	1	3	1	10	1.51	8.41
IRC	Interflow recession parameter	Soils, topography, land use		0.5	0.7	0.3	0.85	0.3	0.54
CEPSC	Interception storage	Veg type/density, land use	Monthly values used	0.03	0.2	0.01	0.4		
CEPJAN								0.03	0.03
CEPFEB								0.03	0.03
CEPMAR								0.03	0.03
CEPAPR								0.08	0.08
CEPMAY								0.12	0.12
CEPJUN								0.12	0.12
CEPJUL								0.12	0.12
CEPAUG								0.12	0.12
CEPSEP								0.12	0.12
CEPOCT								0.06	0.06
CEPNOV								0.03	0.03
CEPDEC								0.03	0.03
LZETP	Lower zone evapotranspiration parameter	Veg type/density, root depth	Monthly values used	0.2	0.7	0.1	0.9		
LZEJAN								0.11	0.11
LZEFEB								0.11	0.11
LZEMAR								0.11	0.11
LZEAPR								0.33	0.33
LZEMAY								0.78	0.78
LZEJUN								0.78	0.78
LZEJUL								0.89	0.89
LZEAUG								0.89	0.89
LZESEP								0.89	0.89
LZEOCT								0.67	0.67
LZENOV								0.22	0.22
LZEDEC								0.22	0.22
Weather Stations									
Monterey Daily								0.35	0.19
Monterey Hourly								0.46	0.34
Lancing								0.87	0.86
C'ville Apt v. Exp Station								0.75	0.99
Kingston								0.24	0.46
North-to-West								0.33	0.40

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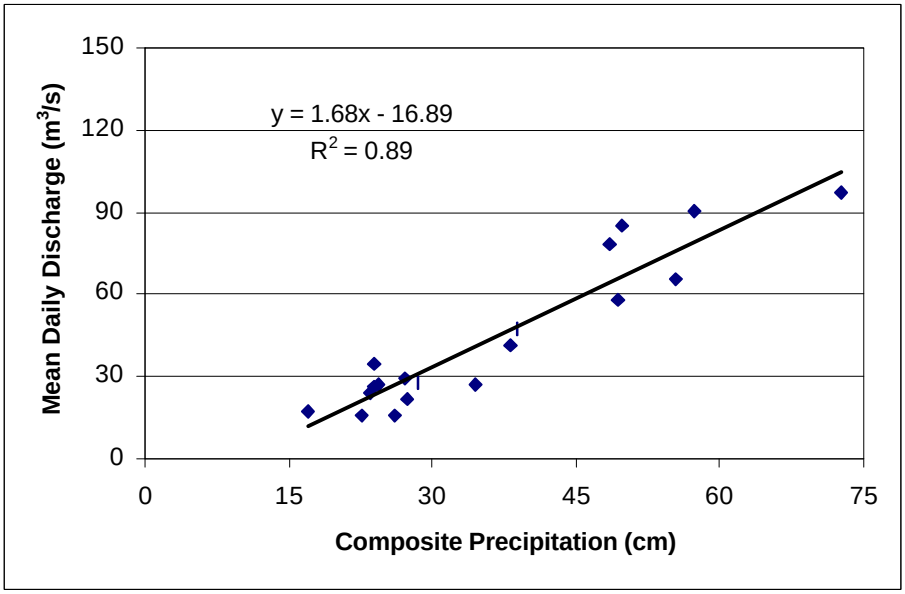


Figure 5.10. Correlation of composite precipitation and Oakdale discharge in the spring

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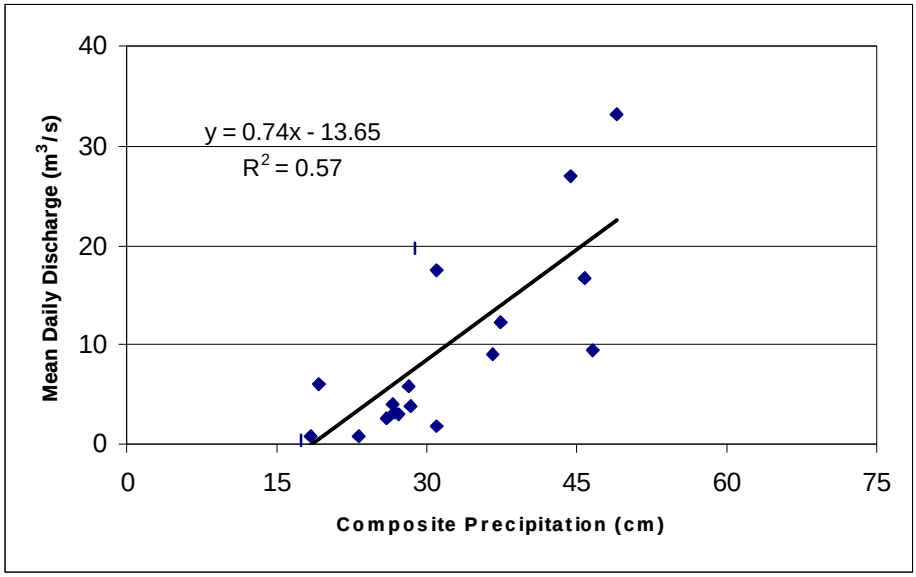


Figure 5.11. Correlation of composite precipitation and Oakdale discharge in the summer

Note: The y-axis scale is not the same as the other graphs of this type.

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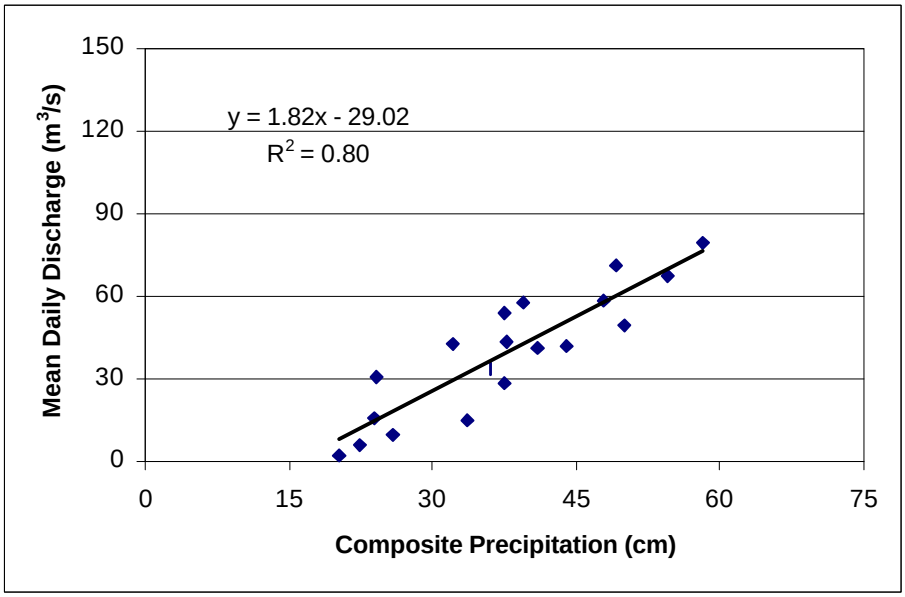


Figure 5.12. Correlation of composite precipitation and Oakdale discharge in the fall

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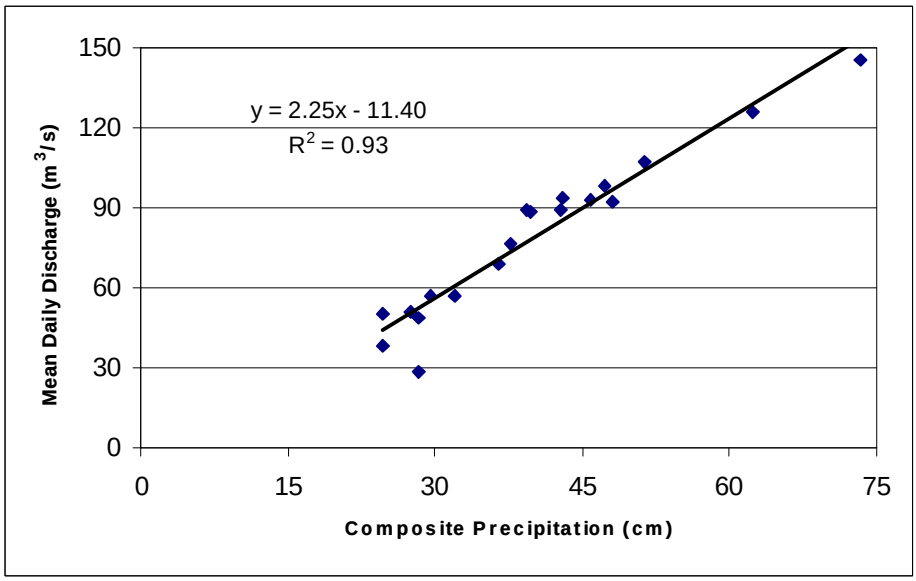


Figure 5.13. Correlation of composite precipitation and Oakdale discharge in the winter

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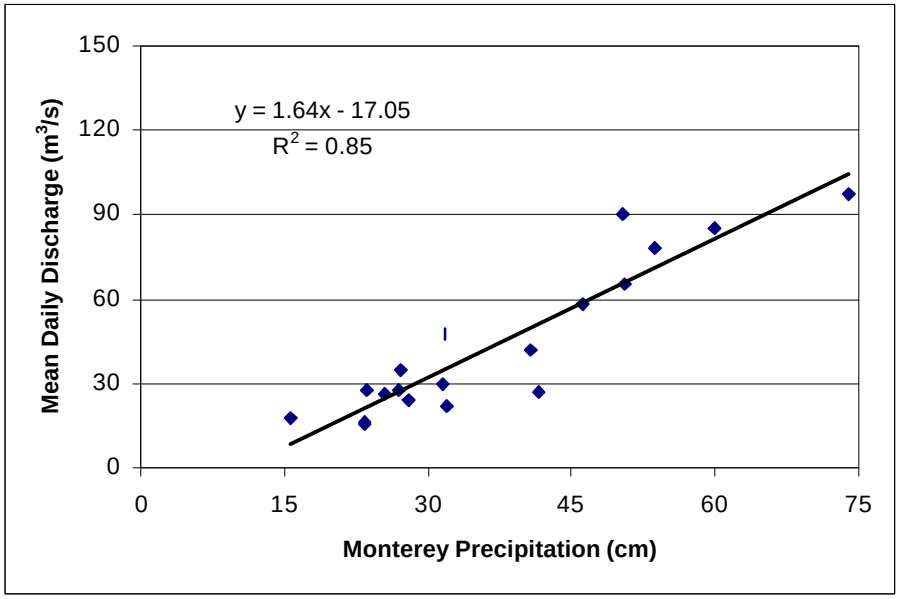


Figure 5.14. Correlation of Monterey precipitation and Oakdale discharge in the spring

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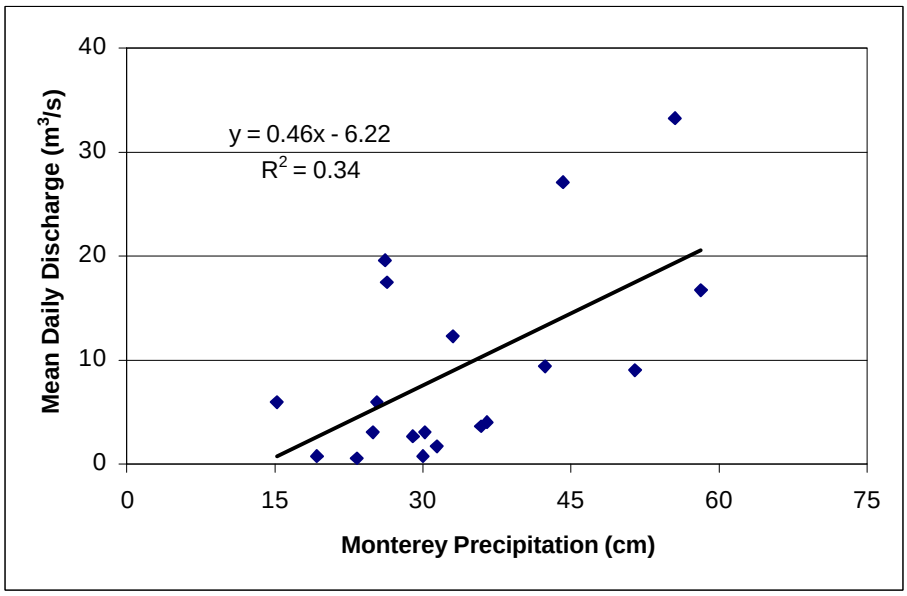


Figure 5.15. Correlation of Monterey precipitation and Oakdale discharge in the summer

Note: The y-axis scale is not the same as the other graphs of this type.

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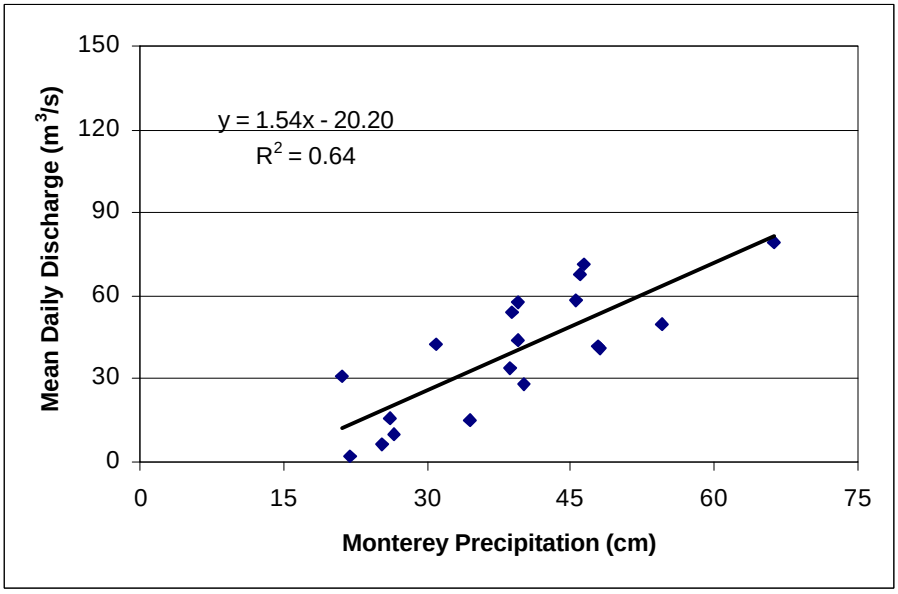


Figure 5.16. Correlation of Monterey precipitation and Oakdale discharge in the fall

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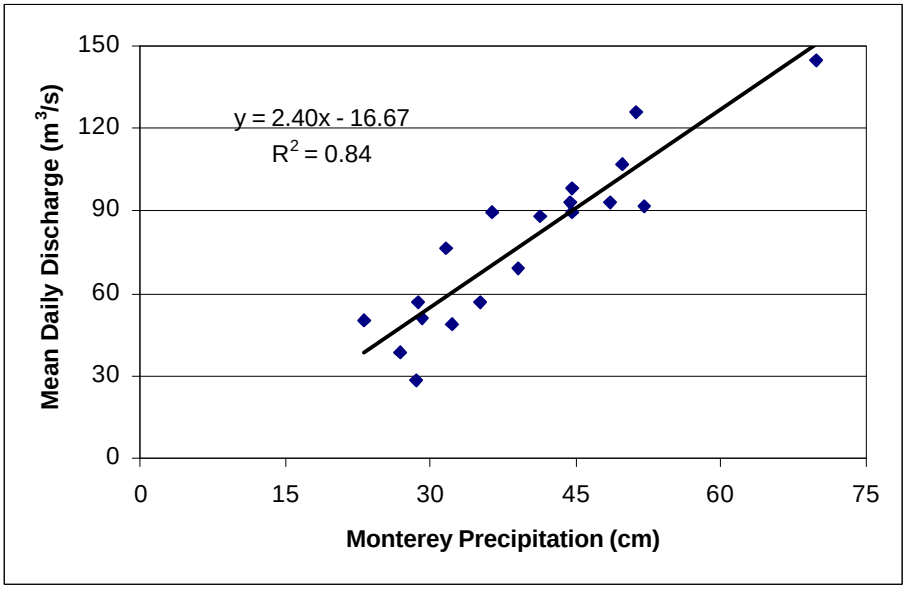


Figure 5.17. Correlation of Monterey precipitation and Oakdale discharge in the winter

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Table 5.11. Weather station weights in Daddy's Creek model

Weather Station	Calibration (1b)	Calibration (1c)	Daddy's Creek
Monterey Daily	0.35	0.19	0.94
Monterey Hourly	0.46	0.34	0.60
Lancing	0.87	0.86	0.42
Crossville Apt vs. Exp Station	0.75	0.99	1.00
Kingston	0.24	0.46	0.23
North-to-West	0.33	0.40	0.21

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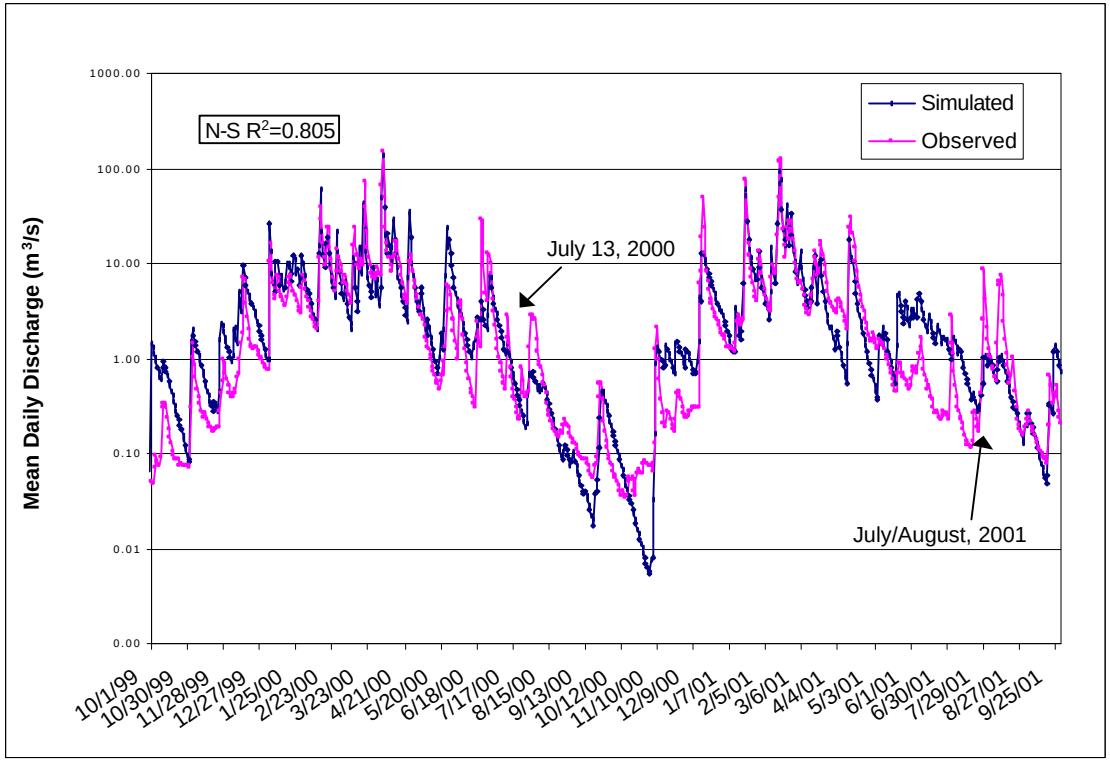


Figure 5.18. Calibration (2a) – Simulated and observed discharge at Hebbertsburg gage using Emory parameters

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Table 5.12. Calibration (2a) – Annual fractional errors in predicted total discharge at the Hebbertsburg gage

Metric	Year 1	Year 2
Fall	**1.35**	-0.14
Winter	-0.04	-0.08
Spring	0.00	-0.10
Summer	-0.11	**5.71**
10% Highest Flows	**-0.26**	**-0.20**
50% Lowest Flows	**1.01**	**2.00**

Note: Bold numerals indicate errors that exceed the TDEC target.

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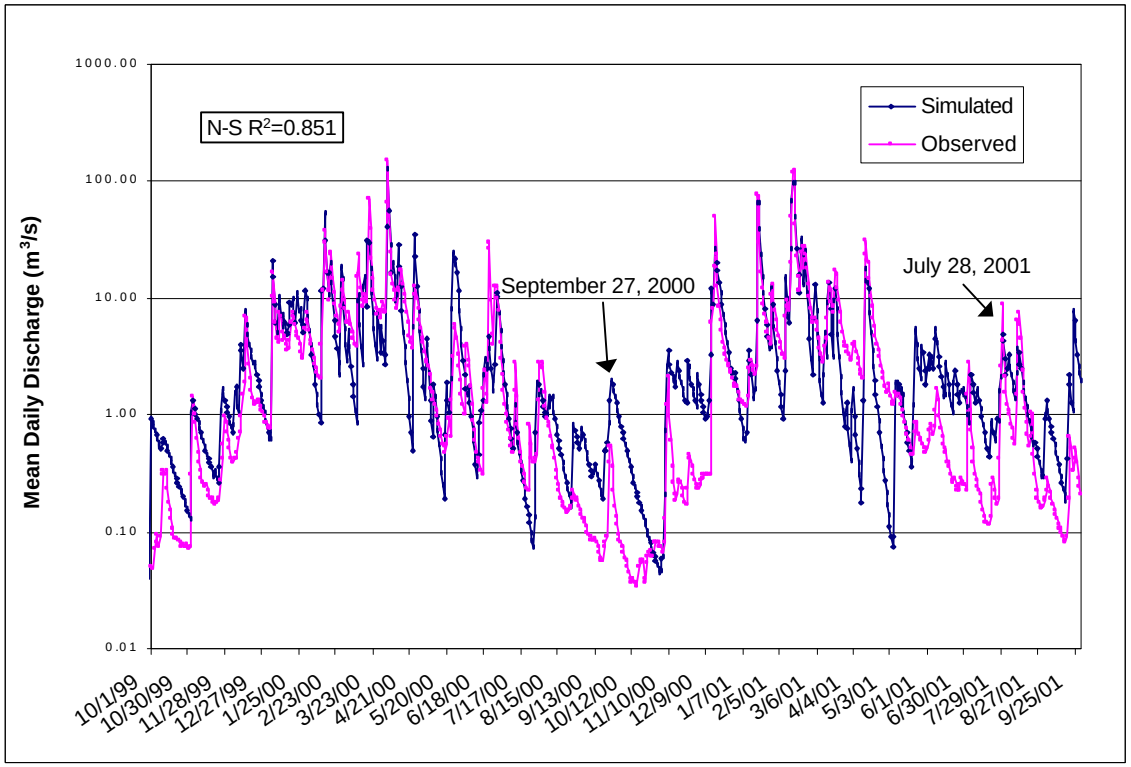


Figure 5.19. Calibration (2b) – Simulated and observed discharge at Hebbertsburg gage using Daddy's Creek parameters

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Table 5.13. Fractional errors using Emory River versus Daddy's Creek parameters

Metric	Emory River Parameters Year 1	Daddy's Creek Parameters Year 1	Emory River Parameters Year 2	Daddy's Creek Parameters Year 2
Fall	**1.35**	**0.79**	-0.14	**0.43**
Winter	-0.04	-0.10	-0.08	-0.10
Spring	0.00	-0.02	-0.10	-0.16
Summer	-0.11	0.28	**5.71**	**0.66**
10% Highest Flows	**-0.26**	**-0.22**	**-0.20**	-0.11
50% Lowest Flows	**1.01**	**0.80**	**2.00**	**3.41**

Note: Bold numerals indicate errors that exceed the TDEC target.

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Table 5.14. Calibration (2b) – Parameter values

Parameter	Description	Function Of	Comments	Typical Min	Typical Max	Possible Min	Possible Max	Emory Calibration (1b)	Daddy's Creek
LZSN	Lower zone nominal soil moisture storage	Soils, climate		3	8	2	15	3.8	5.4
INFILT	Index to infiltration capacity of the soil	Soils, land use	Divides surface/subsurface flow	0.01	0.25	0.001	0.5	0.066	0.060
LSUR	Length of overland flow plane	Topography	Estimate from maps or GIS	200	500	100	700	534	700
SLSUR	Slope of overland flow plane	Topography	Estimate from maps or GIS	0.01	0.15	0.001	0.3	0.07	0.05
KVARY	Groundwater recession flow parameter	Baseflow recession	If recession varies w/ grndwtr lvls	0	3	0	5	0.18	3
AGWRC	Basic groundwater recession rate	Baseflow recession		0.92	0.99	0.85	0.999	0.89	0.95
INFEXP	Exponent in infiltration equation	Soils variability	Usually default to 2	2	2	1	3	2	2
INFILD	Ratio of max to min infiltration capacity	Soils variability	Usually default to 2	2	2	1	3	2	2
DEEPFR	Frac groundwater inflow to deep recharge	Geology, grndwtr recharge		0	0.2	0	0.5	0	0
BASETP	Frac remaining ET from baseflow	Riparian vegetation	Direct ET from riparian vegetation	0	0.05	0	0.2	0	0
AGWETP	Frac remaining ET from active grndwtr strg	Marsh/wetlands extent	Direct ET from shallow groundwater	0	0.05	0	0.2	0	0
UZSN	Upper zone nominal soil moisture strg	Soil conditions, land use	Accounts for near-surface retention	0.1	1	0.05	2	0.82	0.76
NSUR	Manning's n for overland flow	Surface conditions, land use		0.15	0.35	0.1	0.5	0.5	0.35
INTFW	Interflow inflow parameter	Soils, topography, land use	Based on hydrograph separation	1	3	1	10	1.51	3.18
IRC	Interflow recession parameter	Soils, topography, land use		0.5	0.7	0.3	0.85	0.3	0.35
CEPSC	Interception storage	Veg type/density, land use	Monthly values used	0.03	0.2	0.01	0.4		
CEPJAN								0.03	0.03
CEPFEB								0.03	0.03
CEPMAR								0.03	0.03
CEPAPR								0.08	0.08
CEPMAY								0.12	0.12
CEPJUN								0.12	0.12
CEPJUL								0.12	0.12
CEPAUG								0.12	0.12
CEPSEP								0.12	0.12
CEPOCT								0.06	0.06
CEPNOV								0.03	0.03
CEPDEC								0.03	0.03
LZETP	Lower zone evapotranspiration parameter	Veg type/density, root depth	Monthly values used	0.2	0.7	0.1	0.9		
LZEJAN								0.11	0.06
LZEFEB								0.11	0.06
LZEMAR								0.11	0.06
LZEAPR								0.33	0.18
LZEMAY								0.78	0.41
LZEJUN								0.78	0.41
LZEJUL								0.89	0.47
LZEAUG								0.89	0.47
LZESEP								0.89	0.47
LZEOCT								0.67	0.35
LZENOV								0.22	0.12
LZEDEC								0.22	0.12
Weather Stations									
Monterey Daily								0.35	0.94
Monterey Hourly								0.46	0.60
Lancing								0.87	0.42
C'ville Apt v. Exp Station								0.75	1.00
Kingston								0.24	0.23
North-to-West								0.33	0.21

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Table 5.15. Weather station weights in Crooked Fork model

Weather Station	Calibration (1b)	Calibration (1c)	Daddy's Creek	Crooked Fork
Monterey Daily	0.35	0.19	0.94	N/A
Monterey Hourly	0.46	0.34	0.60	0.16
Lancing	0.87	0.86	0.42	N/A
Crossville Apt vs. Exp Station	0.75	0.99	1.00	1
Kingston	0.24	0.46	0.23	0.23
North-to-West	0.33	0.40	0.21	0.46

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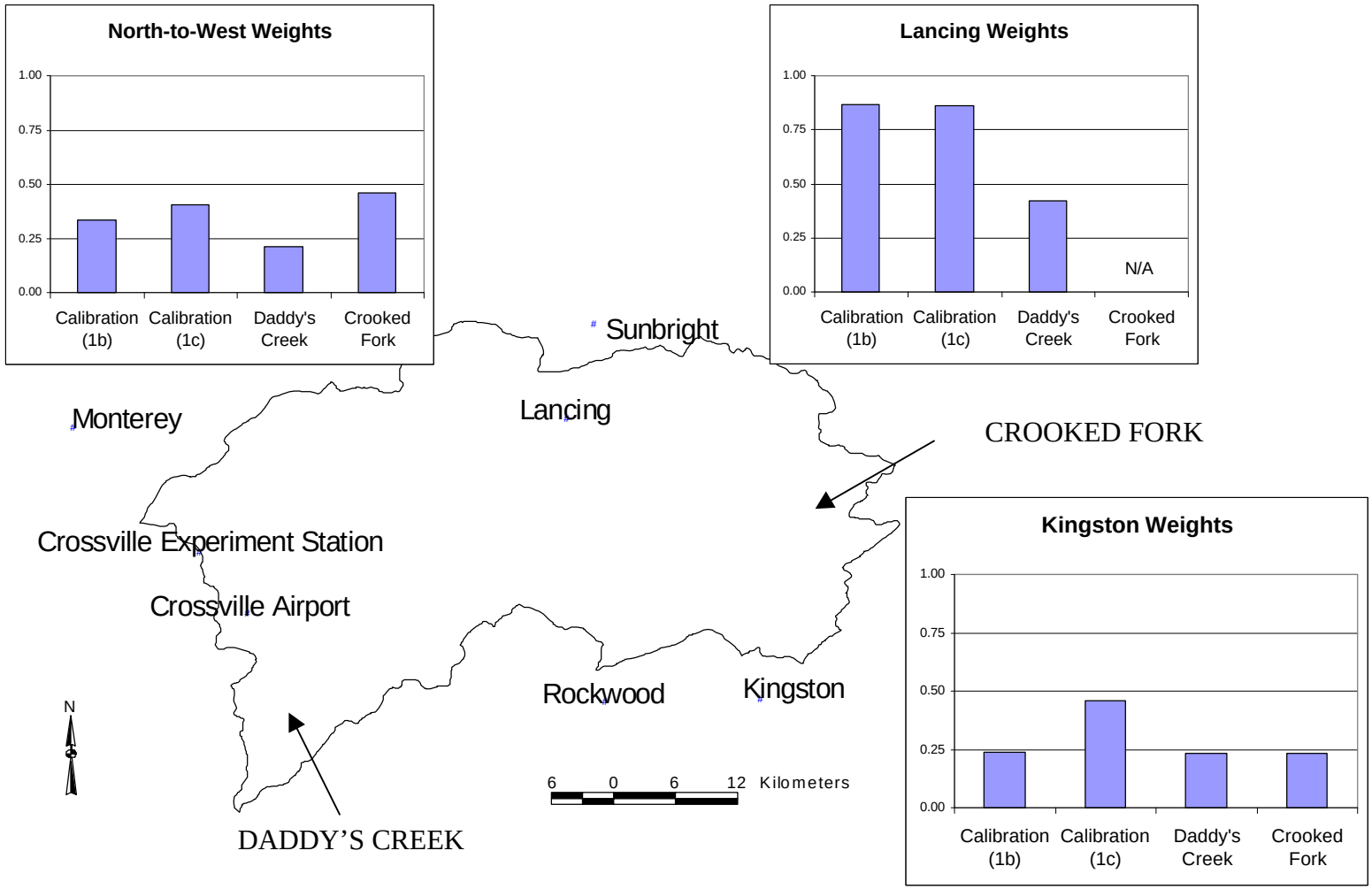


Figure 5.20. Weather station weights in various calibrations

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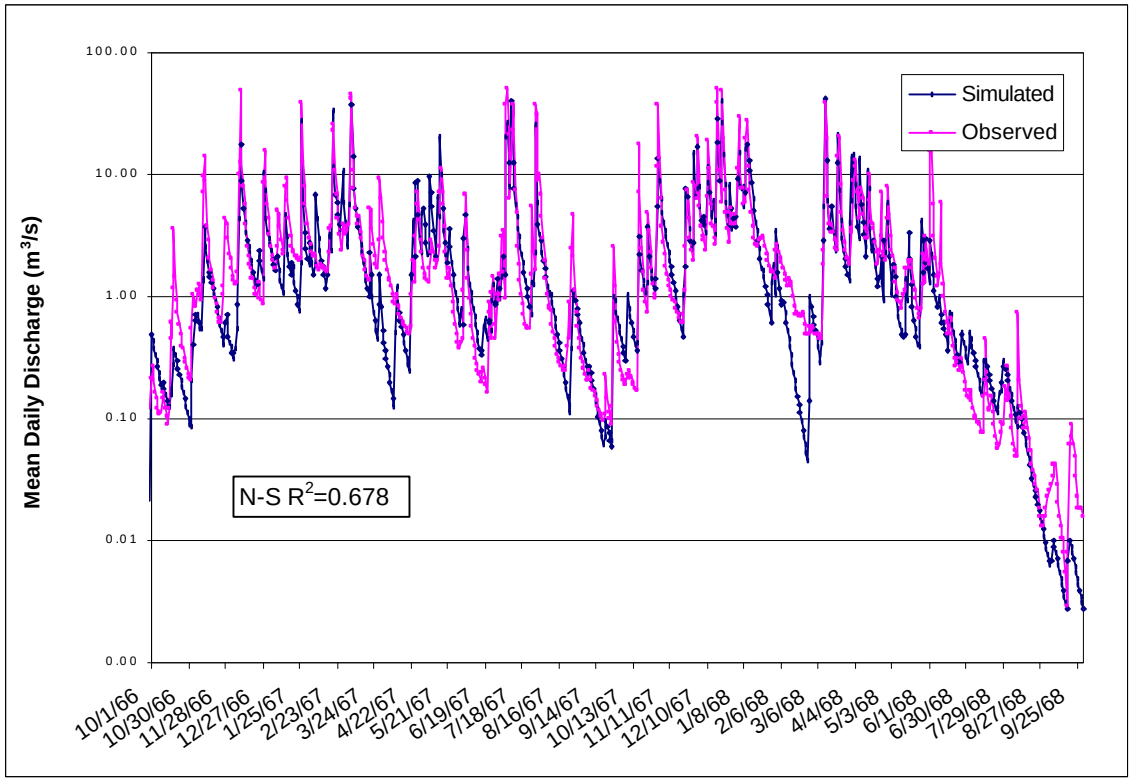


Figure 5.21. Calibration (3a) – Simulated and observed discharge at Wartburg gage using Emory parameters

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Table 5.16. Calibration (3a) – Annual fractional errors at Wartburg gage

Metric	Crooked Fork Year 1	Crooked Fork Year 2	Daddy's Creek Year 1	Daddy's Creek Year 2
Fall	**-0.47**	-0.13	**1.35**	-0.14
Winter	-0.22	-0.12	-0.04	-0.08
Spring	**0.33**	-0.22	0.00	-0.10
Summer	**-0.34**	**0.34**	-0.11	**5.71**
10% Highest Flows	**-0.37**	**-0.32**	**-0.26**	**-0.20**
50% Lowest Flows	0.10	0.05	**1.01**	**2.00**

Note: Bold numerals indicate errors that exceed the TDEC target.

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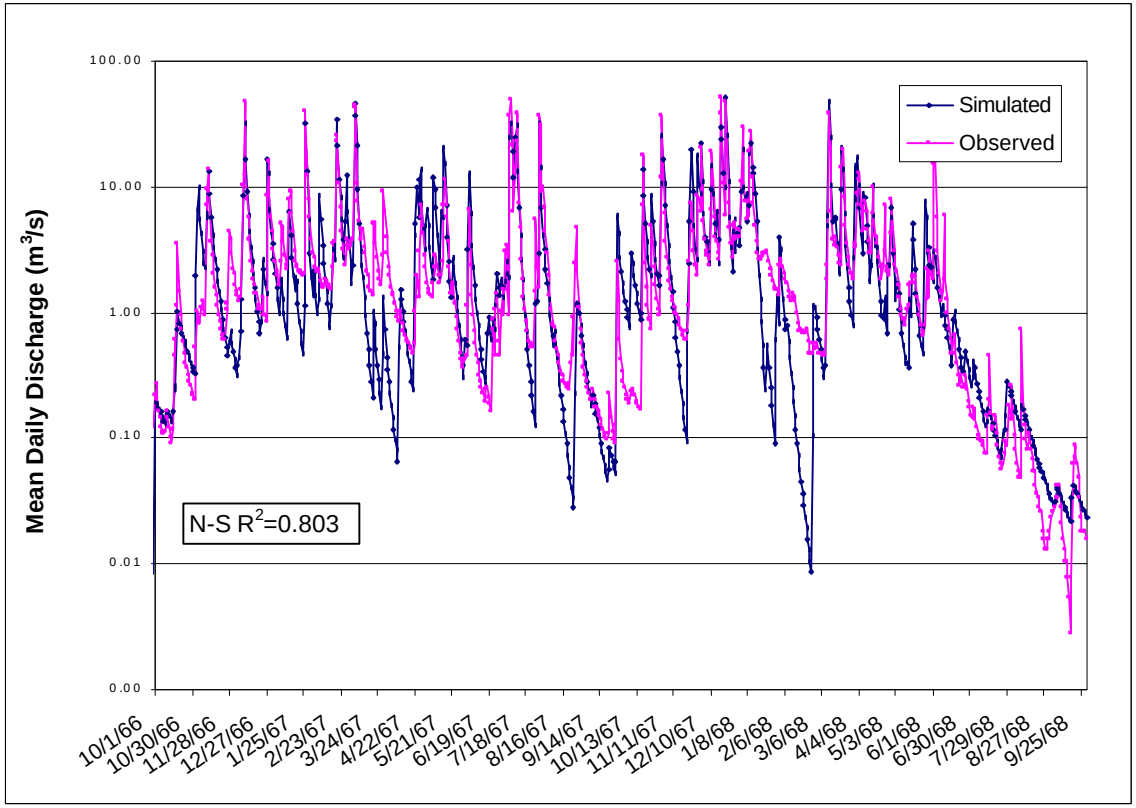


Figure 5.22. Calibration (3b) – Simulated and observed discharge at Wartburg gage using Crooked Fork parameters

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Table 5.17. Calibration (3b) – Annual fractional errors at Wartburg gage

Metric	Emory River Parameters Year 1	Crooked Fork Parameters Year 1	Emory River Parameters Year 2	Crooked Fork Parameters Year 2
Fall	**-0.47**	0.02	-0.13	0.27
Winter	-0.22	-0.16	-0.12	-0.05
Spring	**0.33**	**0.76**	-0.22	-0.12
Summer	**-0.34**	-0.23	**0.34**	**0.33**
10% Highest Flows	**-0.37**	-0.13	**-0.32**	-0.10
50% Lowest Flows	0.10	**0.47**	0.05	**0.34**

Note: Bold numerals indicate errors that exceed the TDEC target.

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Table 5.18. Calibration (3b) – Observed discharge and fractional errors at Wartburg gage

Metric	Mean Daily Discharge in Year 1 (m3/s)	Fractional Prediction Error in Year 1	Mean Daily Discharge in Year 2 (m3/s)	Fractional Prediction Error in Year 2
Fall	2.7	0.02	5.5	0.27
Winter	5.4	-0.16	4.3	-0.05
Spring	1.6	**0.76**	2.9	-0.12
Summer	4.0	-0.23	0.1	**0.33**
10% Highest Flows	19.3	-0.13	17.9	-0.10
50% Lowest Flows	0.6	**0.47**	0.3	**0.34**

Note: Bold numerals indicate errors that exceed the TDEC targets.

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Table 5.19. Calibration (3b) – Parameter values

Parameter	Description	Function Of	Comments	Typical Min	Typical Max	Possible Min	Possible Max	Emory Calibration (1b)	Crooked Fork
LZSN	Lower zone nominal soil moisture storage	Soils, climate		3	8	2	15	3.8	2.0
INFILT	Index to infiltration capacity of the soil	Soils, land use	Divides surface/subsurface flow	0.01	0.25	0.001	0.5	0.066	0.137
LSUR	Length of overland flow plane	Topography	Estimate from maps or GIS	200	500	100	700	534	600
SLSUR	Slope of overland flow plane	Topography	Estimate from maps or GIS	0.01	0.15	0.001	0.3	0.07	0.12
KVARY	Groundwater recession flow parameter	Baseflow recession	If recession varies w/ grndwtr lvls	0	3	0	5	0.18	2.80
AGWRC	Basic groundwater recession rate	Baseflow recession		0.92	0.99	0.85	0.999	0.89	0.96
INFEXP	Exponent in infiltration equation	Soils variability	Usually default to 2	2	2	1	3	2	2
INFILD	Ratio of max to min infiltration capacity	Soils variability	Usually default to 2	2	2	1	3	2	2
DEEPFR	Frac groundwater inflow to deep recharge	Geology, grndwtr recharge		0	0.2	0	0.5	0	0
BASETP	Frac remaining ET from baseflow	Riparian vegetation	Direct ET from riparian vegetation	0	0.05	0	0.2	0	0
AGWETP	Frac remaining ET from active grndwtr strg	Marsh/wetlands extent	Direct ET from shallow groundwater	0	0.05	0	0.2	0	0
UZSN	Upper zone nominal soil moisture strg	Soil conditions, land use	Accounts for near-surface retention	0.1	1	0.05	2	0.82	0.2
NSUR	Manning's n for overland flow	Surface conditions, land use		0.15	0.35	0.1	0.5	0.5	0.5
INTFW	Interflow inflow parameter	Soils, topography, land use	Based on hydrograph separation	1	3	1	10	1.51	10
IRC	Interflow recession parameter	Soils, topography, land use		0.5	0.7	0.3	0.85	0.3	0.3
CEPSC	Interception storage	Veg type/density, land use	Monthly values used	0.03	0.2	0.01	0.4		
CEPJAN								0.03	0.03
CEPFEB								0.03	0.03
CEPMAR								0.03	0.03
CEPAPR								0.08	0.08
CEPMAY								0.12	0.12
CEPJUN								0.12	0.12
CEPJUL								0.12	0.12
CEPAUG								0.12	0.12
CEPSEP								0.12	0.12
CEPOCT								0.06	0.06
CEPNOV								0.03	0.03
CEPDEC								0.03	0.03
LZETP	Lower zone evapotranspiration parameter	Veg type/density, root depth	Monthly values used	0.2	0.7	0.1	0.9		
LZEJAN								0.11	0.06
LZEFEB								0.11	0.06
LZEMAR								0.11	0.06
LZEAPR								0.33	0.18
LZEMAY								0.78	0.41
LZEJUN								0.78	0.41
LZEJUL								0.89	0.47
LZEAUG								0.89	0.47
LZESEP								0.89	0.47
LZEOCT								0.67	0.35
LZENOV								0.22	0.12
LZEDEC								0.22	0.12
Weather Stations									
Monterey Daily								0.35	N/A
Monterey Hourly								0.46	0.16
Lancing								0.87	N/A
C'ville Apt v. Exp Station								0.75	1
Kingston								0.24	0.23
North-to-West								0.33	0.46

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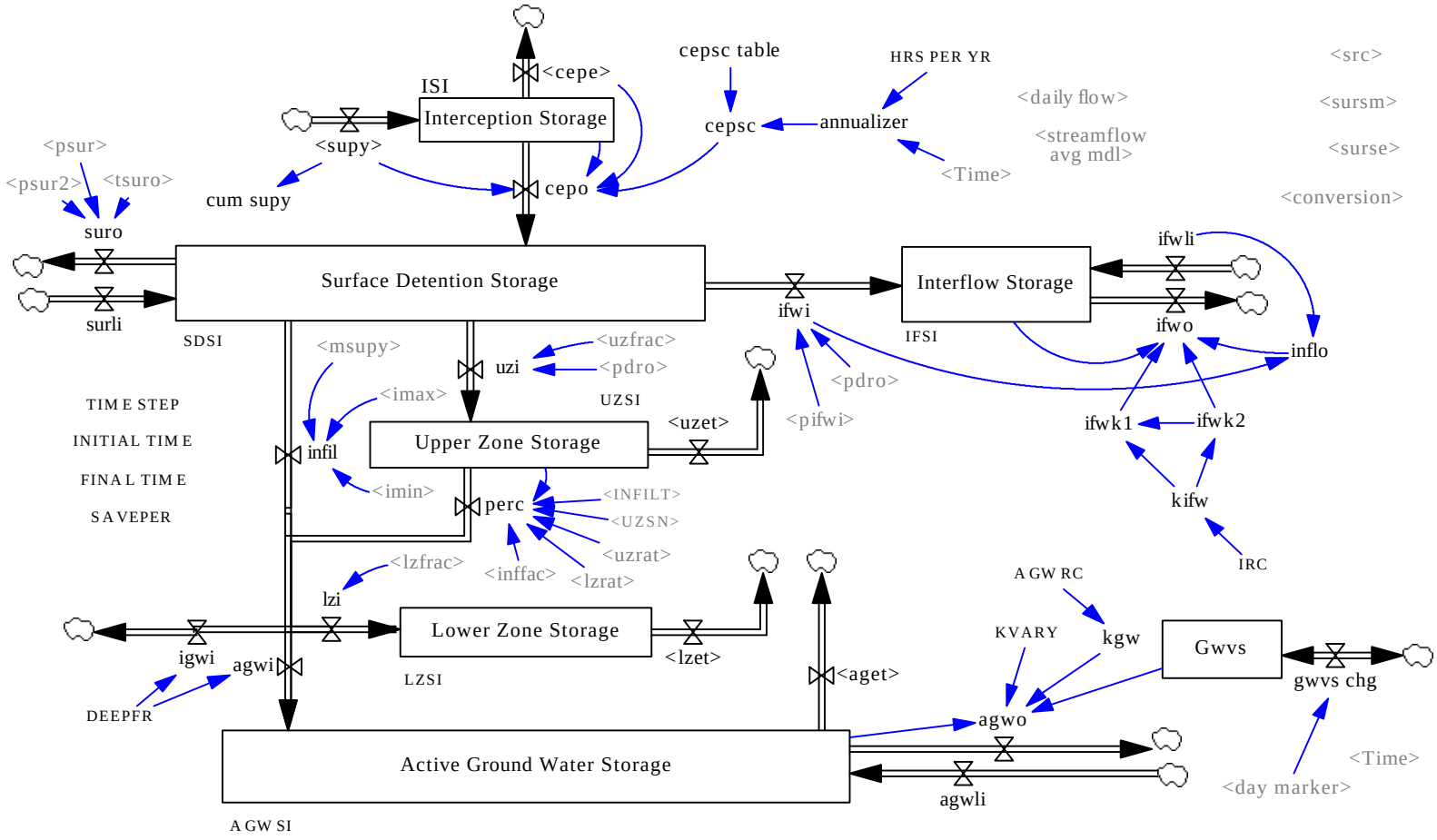


Figure A.1. VenSWM hydrology schematic

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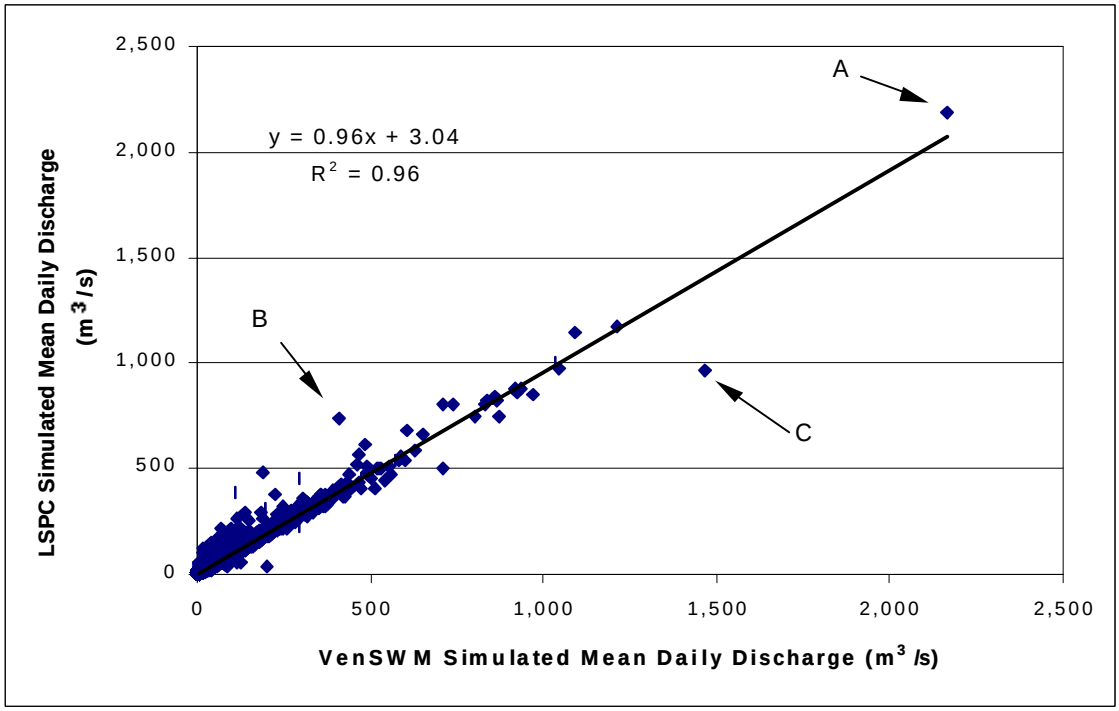


Figure B.1. Comparison of LSPC and VenSWM simulated discharge, 1980-1998

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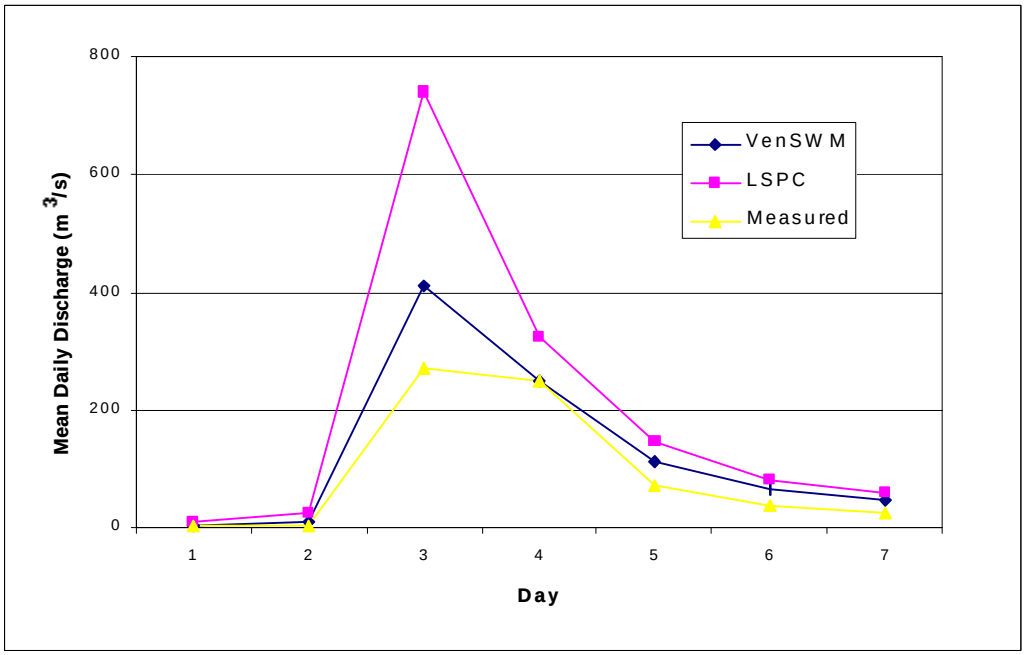


Figure B.2. LSPC and VenSWM simulated discharge and observed discharge for point B

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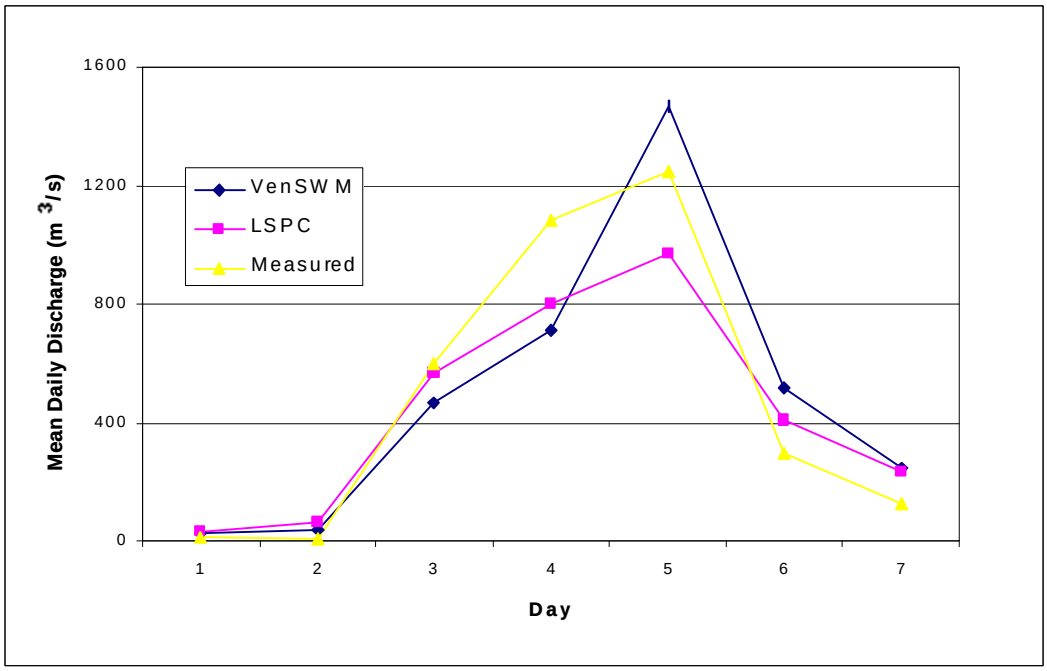


Figure B.3. LSPC and VenSWM simulated discharge and observed discharge for point C

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Vita

Benjamin Bryan Arthur grew up in Oak Ridge, Tennessee, and graduated from Oak Ridge High School. He received a Bachelor of Arts degree from the University of Texas, majoring in economics and history. He returned to school to pursue a Master of Science degree in geography after several years working as an analyst for an insurance company and a consulting company. He currently works as a data analyst in international market research at Merck.