

COMPARISON OF INPUT PRECIPITATION SOURCES IN STREAMFLOW FORECASTING

by

BRIAN KEITH AVANT

(Under the direction of Todd C. Rasmussen)

ABSTRACT

Hydrologic modeling requires meteorologic and landscape data as inputs for streamflow forecasting and prediction. While many remote areas lack adequate ground-based data for model calibration and use, remotely sensed (e.g., satellite) data can provide the information needed for global applications. Sources of remotely sensed meteorologic data include TRMM, GPM, and GRACE, as well as reanalysis data, such as MERRA and GLDAS. This study investigates the accuracy of hydrologic modeling when satellite data are used in place of ground-based meteorological data. A spatially distributed streamflow model, Hydrologic Simulation Program-FORTRAN (HSPF), is used to model six watersheds (2,315 to 11,400 km²) in the Coastal Plain and Piedmont physiographic provinces of the Southeastern United States. Observed streamflow is compared with modeled streamflow using meteorologic data from both ground-based and satellite sources. The fitting error and bias were computed for each input product/method scenario using BASSET, a baseflow separation program developed for this study. TRMM precipitation and MERRA potential evapotranspiration data are shown to be suitable substitutes for ground-based meteorological data for the watersheds examined. TRMM/MERRA coupled inputs actually perform better (i.e., provide a better fit to observed data) than ground-based inputs for the largest watershed modeled.

INDEX WORDS: precipitation, streamflow, hydrologic modeling, TRMM, MERRA,
HSPF, PEST, BASINS

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Preface

Coursework in the Warnell School of Forestry and Natural Resources shaped me into a hydrologist and I am very satisfied with the result of my time here.

Athens, December 2013

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List of Abbreviations

BASINS	Better Assessment Science Integrating point & Non-point Sources
BASSET	BASeFlow SEparation Tool
GLDAS	Global Land Data Assimilation System
GPM	Global Precipitation Mission
GRACE	Gravity Recovery & Climate Experiment
HSPF	Hydrologic Simulation Program, FORTRAN
MAE	Mean Absolute Error, a measure of model performance
MERRA	Modern Era Retrospective-Analysis for Research and Applications
mNSE	Modified Nash-Sutcliffe Efficiency, a measure of model performance
NASA	National Aeronautics and Space Administration
NSE	Nash-Sutcliffe Efficiency, a measure of model performance
NN	Nearest Neighbor method for assigning precipitation
R^2	Correlation coefficient, a measure of model performance
RMSE	Root mean squared error, a measure of model performance
SG	Segmented method for assigning precipitation
TRMM	Tropical Rainfall Monitoring Mission
WA	Weighted Average method for assigning precipitation
WMS	Watershed Modeling System

Chapter 1

Introduction

1.1 Motivation

Streamflow prediction is an essential component of environmental planning and management. Decision makers rely on predictions from hydrologic models for flood and drought forecasting, civil design applications, and basin management. Improvements in modeling contribute to the overall understanding of basin function and how individual processes interact to produce hydrologic responses to watershed changes in the basin (Blöschl 2006). Understanding a watershed's behavior could enable faster warnings during extreme events, minimizing damage to property and loss of life. Characterizing a watershed's behavior can also shed further insight into the effects caused by land use and climate related changes.

Minimizing prediction uncertainties remains a major obstacle in modeling river discharges, and arises in many stages of the modeling process. The three major sources of uncertainty in the modeling process include input data, model structure, and observed comparison data. The first, specifically precipitation data, has a major effect on streamflow prediction and is associated primarily with low density of gauge networks.

Remotely Sensed Meteorologic Data

Many remote areas of the world suffer from sparse or absence of ground-based observed meteorological and hydrologic data. The availability of remotely sensed climatological data has enabled hydrologic modeling and improved streamflow estimation in watersheds that lack or have sparse networks of data. In addition to meteorological data, model calibration requires either discharge data from stream gauges or detailed information about watershed hydrologic properties. Unfortunately, these data are often unavailable, especially in remote or inaccessible watersheds.

Even areas with abundant resources such as the United States are affected by data limitations. Stokstad (1999) noted that stream and rainfall gauges are in steady decline globally. Even in areas where science budgets are robust, long-term continuous datasets seem to be a low priority. Compounding the issue is that gauges that are most important (remote areas, hard to get to) are the most expensive to maintain and are therefore deactivated first.

Prediction in Ungauged Basins

In 2002, the International Association of Hydrological Sciences (IAHS) launched the Prediction in Ungauged Basins (PUB) program, a decade-long initiative with a goal to improve the predictive capacity of hydrology in order to meet society's basic hydrological needs (Sivapalan 2003, Takeuchi 2004). The PUB project was promoted through a grassroots discussion among the hydrologic science community. PUBs aim was to reduce and deliver the best-available predictive capacity to users with poor or nonexistent water resource management plans. A plethora of discussions, conferences, and papers have been produced and as a result of the initiative and water-related policies around the world are making positive steps forward.

In a joint project between Savannah River National Laboratory (SRNL) and University of Georgia (UGA), a study was conducted that focused on generating inland flows and routing them to coastal systems. The UGA component of the project was to develop a hydrological modeling framework for predicting river discharges and contaminant transport in data-poor regions. The research accomplished this goal by developing methods for exploring variability in flow and transport in remote areas of the world, where monitoring networks are either sparse or non-existent. The study used the data-rich Savannah River watershed, which forms the border between South Carolina and Georgia, to develop a methodology for areas with less-abundant observational resources.

A number of studies have shown the potential for using remote sources of input data to drive hydrologic models. A recent study in the Piedmont region compared high-resolution NEXRAD precipitation to weather station data for two subbasins of the Neuse River in North Carolina (Price et al. 2013). Results indicate that NEXRAD data provides more-accurate streamflow predictions than traditional, ground-based data. While many studies have used remote data to predict streamflow, it has not been shown what input method is best for different drainage basin scales.

Research Location

This research focuses on watersheds in the Coastal Plain and Piedmont physiographic provinces in the Southeastern United States. The Coastal Plain physiographic province spans from Texas to New Jersey. The region consists of late-Cretaceous to Holocene sedimentary rocks, which were deposited in a marine environment then subsequently uplifted. Hydrologically, the Coastal Plain is dominated by robust karstic groundwater aquifers. The Piedmont physiographic province lies between the Appalachian Mountains and Coastal Plain, and spans from Alabama to Pennsylvania. The Piedmont is a highly weathered landscape that is underlain by crystalline bedrock. Flow is dominated by shallow (surficial) ground water and

surface water. Flow through the underlying fractured crystalline bedrock is a relatively minor component of regional flow.

1.2 Problem Statement

The objective of this research is to evaluate the suitability of substituting traditional ground-based meteorological data with satellite-derived precipitation and evapotranspiration data in hydrologic modeling. An additional objective is to determine whether the suitability is a function of basin size.

This research distinguishes itself from previous studies in three ways:

- First, coupling TRMM and MERRA data to drive a hydrologic model for streamflow prediction has not been done to date. Previous papers discuss the predictive abilities of both TRMM and MERRA and have even used their precipitation inputs individually in hydrologic models. TRMM does not have a potential evapotranspiration product which limits the ability to drive a model completely independent of ground-based data. By coupling these products, it allows the user the ability to predict streamflow without ground-based stations on a near-global scale.
- Additionally, this study examines the best methods for inputting climatological data from an end users standpoint. The general and easiest method of climatological input selection for ground-based stations is to select the closest station with data available during the period of calibration. BASINS has the option to segment the model into hydrologically homogenous sections, though often times ground-based stations are spatially sparse or do not contain adequate overlapping data sets. The advantage to remotely sensed products is that they are spatially uniform, which allows for a more accurate data set for model inputs.

- Finally, basin scale and its effect on product accuracy and input methods is addressed. Climatological data sets are highly susceptible to scale of the watershed. Examining the effects scale have on the previous two focus points will help to understand the big picture when applying these techniques to a wide range of watersheds.

The main questions this paper wishes to address are:

- Do MERRA and TRMM/MERRA remotely sensed input data sets produce accurate streamflow predictions compared to traditional ground-based data?
- Does the input method of climatological data have a significant effect on streamflow predictions? Does this change with the input product?
- Are the results of the previous two questions affected by the basin scale of the area of study?

1.3 Approach

BASINS

This study utilizes BASINS (Better Assessment Science Integrating Point and Non-Point Sources), which is an environmental analysis system used for watershed and water quality assessment. BASINS was developed and is maintained by the U.S. Environmental Protection Agency. The newest version (4.1) uses an open-source GIS software architecture that supports standard GIS file formats, which facilitates sharing of files and datasets from similar GIS software. BASINS integrates numerous sources of data with analysis tools making it easy to perform environmental assessments and calculate TMDL (Total Maximum Daily Loads).

BASINS also uses mapwindow to allow for *plug-ins* of programs like HSPF (Hydrologic Simulation Program - FORTRAN), which is used to simulate stream discharge (Bicknell et al. 2001). HSPF also has the ability to incorporate reservoirs in watershed streamflow predictions, as well as simulate tracer movement. HSPF was selected as the modeling framework for this study because of its ability to incorporate remotely sensed meteorological data using the utility `WDMUtil`, in which time series of various meteorological data are imported at the timescale of choice. The model has been well cited in both the United States (Chen 2004; Filoso et al. 2004; Duda et al. 2012; He and Hogue 2012; Patil and Deng 2012) as well as globally (Hayashi et al. 2004; Akter and Babel 2012; Ciou et al. 2012).

Data Sources

Hydrologic models were developed for six watersheds in the Southeastern Coastal Plain and Piedmont physiographic provinces (Figure 1.1). These watersheds were chosen because of the abundance of continuous hydrological and meteorological data, as well as their similar land-use characteristics, watershed areas, and meteorological conditions.

Meteorological inputs were obtained from ground-based stations, as well as from remotely sensed data. NASA's newest release of TRMM 3B-42 data (Version 7) were used, providing one of the first applications of these data. Meteorologic data were incorporated using three input methods; a) nearest neighbor (NN), b) segmented (SG), and c) areally weighted (WA).

Organization

This manuscript is organized with a literature review in Chapter 2, a summary of the analysis methods and site description in Chapter 3, results in Chapter 4, discussion in Chapter 5, and conclusions in Chapter 6.

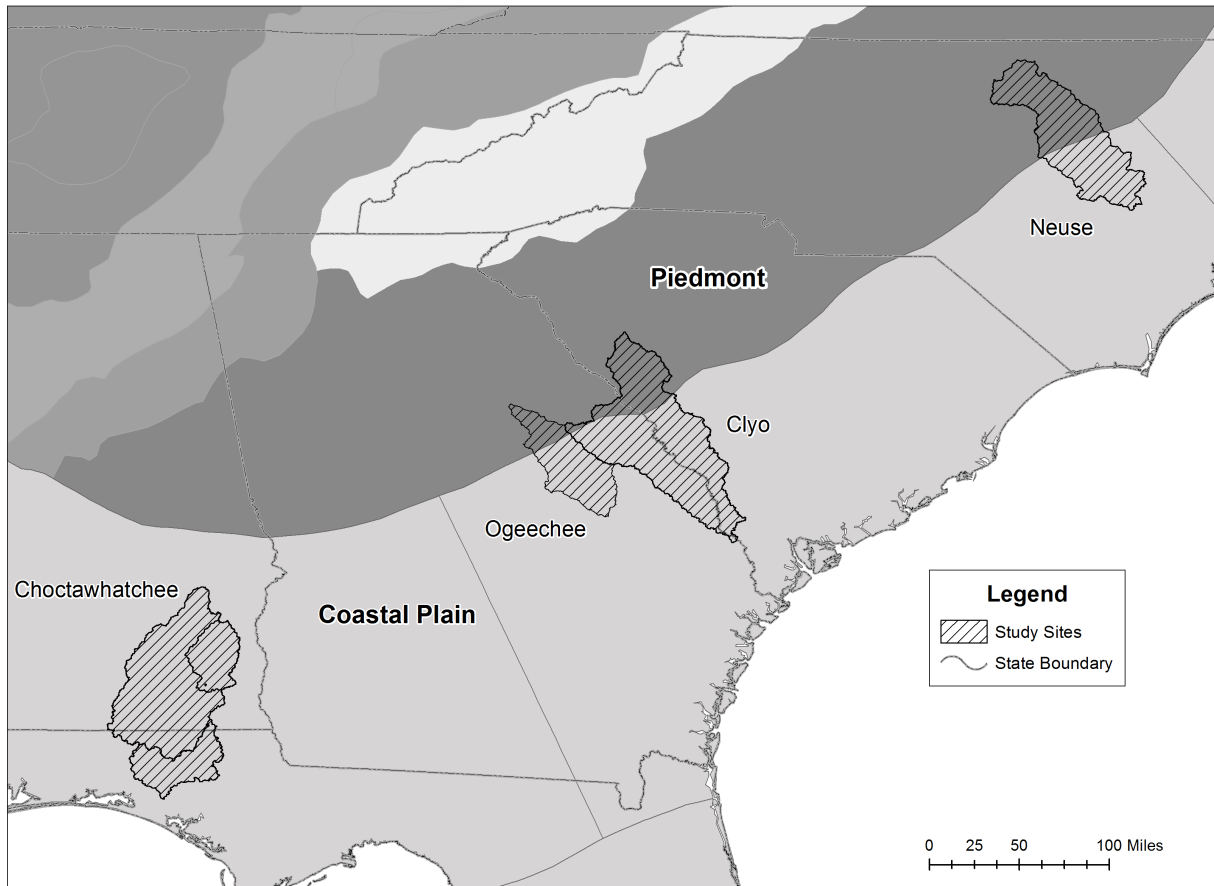


Figure 1.1: Locations of six watersheds modeled using BASINS/HSPF. Each watershed model was compared using two types of meteorological inputs, remotely sensed and ground-based. Also shown are the Piedmont and Coastal Plain physiographic provinces in the Southeastern United States.

Chapter 2

Literature Review

This chapter reviews the underlying concepts of the modeling process. Sections include the application in broader context, uncertainty, input sources, types of models, calibration, and model evaluation.

2.1 Modeling in Ungauged Basins

According to the IAHS (Sivapalan 2003) an ungauged basin is defined by:

“Any basin with inadequate records, in both quality and quantity, of hydrological observations to enable computation of hydrological variables of interest, water quantity or quality, at the appropriate spatial and temporal scales, and to the accuracy acceptable for practical applications.”

In this thesis, the term is limited to predicting only one hydrological variable, streamflow. Input data sources with varying spatial resolution are applied to a selected hydrologic model to determine their respective predictive capabilities over a representative time span. Though the basins used in this study are not true ungauged basins, the analyses employed in this study will help improve the methodology used to successfully model ungauged basins.

2.2 Uncertainties in Modeling

Three major sources of uncertainty exist in the modeling process: input data, model structure, and observed comparison data. In order to successfully calibrate and use model simulations for decision-making processes, these uncertainties must be minimized as much as possible.

Model Input Uncertainty. The first major source of uncertainty is the input data that drives the hydrologic model. Meteorological data is the initial source of uncertainty in the modeling process. Consisting of precipitation and other climatological factors (e.g. potential evapotranspiration, solar radiation, wind data, and cloud cover) are subject to large amounts of uncertainty due to spatial interpolation.

In addition to meteorological input data, our modeling system requires land-surface conditions and topography for determining drainage basins and other hydrologically relevant factors. These data sets can also have a major effect on a models outcome, but are rarely discussed in papers.

Minimizing uncertainty in input data sets is accomplished by the use of reliable data, proper acquisition, and maximizing spatial resolution.

Model Structure Uncertainty. A single model often lacks the ability to completely capture the complexities of physical processes within a hydrologic basin. Model uncertainty occurs due to structural noise in the conceptual model as it attempts to simulate this reality. The inevitable simplification of reality to conceptual model means that model parameters can be difficult or impossible to measure directly and can contain interdependencies between each other (Sivapalan 2003). Calibration of these conceptual parameters are then subject to equifinality, or the ability have multiple calibration parameter sets that satisfy objective criteria for calibration (Beven 1993). This nonuniqueness of parameter sets results from the

errors and uncertainty in data as well as the conceptual model (Beck 1987). Hydrologic models should be calibrated in parameter sets instead of by individual parameter values because of these uncertainties (Doherty et al. 2003).

Observed Comparison Data Uncertainty. Finally, the data used to calibrate or evaluate a model's performance is just as susceptible to uncertainty as the input sources. A study by Pelletier (1988) found that overall uncertainty in a single determination of river discharge, at the 95 percent confidence level, can vary in the range 8 to 20 percent. Observed data sets that have been interpolated records with gaps in time or that have been disaggregated to timescales with finer resolutions than the original should be considered in the evaluation process.

2.3 Input Data

This section summarizes two types of available data, remotely sensed data and re-analysis data. Re-analysis data are obtained by filtering observed data (both ground-based and remotely sensed) through numerical models to provide a best estimate of hydrometeorological conditions. Remotely sensed data, on the other hand, have not been filtered.

Re-Analysis Tools

Retrospective-analyses (or reanalyses) blend the continuity and breadth of output data of a numerical model with the constraint of observational data. The result is a long-term continuous data record. Two re-analysis tools are discussed, MERRA and GLDAS.

Modern Era Retrospective-Analysis for Research and Applications

A useful meteorological data source is the National Aeronautics and Space Administration (NASA) Modern Era Retrospective-Analysis for Research and Applications (MERRA) re-analysis product¹. MERRA was developed to support NASA's Earth Science objectives, by applying the state-of-the-art Global Modeling and Assimilation Office (GMAO) data assimilation system that includes many modern observing systems in a climate framework.

Global Land Data Assimilation System

The Global Land Data Assimilation System (GLDAS) produces land surface states and fluxes using multiple land surface models (LSM) and data assimilation techniques. LSMs are driven by satellite and ground based observation datasets. GLDAS runs globally at a 0.25° resolution and produces results in near-real time. Data from 2001-present is publicly available for use in driving weather and climate prediction models (Rodell et al. 2004).

Remote Sensing Tools

Remotely sensed data are available from a wide range of satellite platforms, including TRMM, GPM, and GRACE.

Tropical Rainfall Measuring Mission

Another useful data source is the NASA Tropical Rainfall Measuring Mission (TRMM) satellite platform. The combined instrument rain calibration algorithm (3B-42) uses an optimal combination of combined NASA TRMM Precipitation Radar (PR) and Microwave Imager (TMI), DoD Special Sensor Microwave-Imager (SSM/I), EOS Advanced Microwave Scanning Radiometer (AMSR) and Advanced Microwave Sounding Unit (AMSU) precipitation

¹<http://gmao.gsfc.nasa.gov/research/MERRA/>

estimates, to adjust infrared (IR) satellite imagery estimates from geostationary (GOES) observations.

Near-global estimates are made by calibrating the IR brightness temperatures to the microwave-based estimates (Huffman et al. 2007). The TMPA 3B-42 Version 7 estimates are scaled to match the monthly rain gauge analyses used in 3B-42. The output is rainfall for $1/4^\circ \times 1/4^\circ$ grid boxes every three hours covering the area between 50°N - 50°S . Data is available from 1998 to present, although there is currently a delay to real-time data due to processing.

Moffit et al. (2011) analyzed the benefit of using the TRMM-based Flood Detection System (FDS) to address transboundary river flooding in Bangladesh. The FDS uses TMPA-based rainfall in a near real-time hydrologic model that determines the runoff depth generated along a calculated flow path with a metric value for flood potential (Hong et al. 2007). They showed that 3B42V6 can be effective in estimating rainfall trends in the ground data in Bangladesh. Ebert et al (2007) produced similar results for the probability of 3B42V6 predicting rainfall. The authors conclude that 3B42V6 underestimates ground-based rainfall data by about 11.6 percent. Another study by Tian et al. (2007) showed that 3B42V6 generally overestimated rainfall for the contiguous United States.

Global Precipitation Measurement

The Global Precipitation Measurement (GPM) mission, initiated by NASA and JAXA, is an international network of satellites that will provide global observations of rain and snow. Scheduled to launch in 2014, GPM will build upon the success of TRMM with improved accuracy, coverage and dynamic range for studying precipitation characteristics. The GPM concept centers on the deployment of a Core Observatory carrying the first space-borne Ku/Ka-band Dual-frequency Precipitation Radar (DPR) and a multi-channel GPM Microwave Imager (GMI) to measure precipitation from space and serve as a reference stan-

dard to unify precipitation measurements from a constellation of research and operational satellites (Smith 2007; Neeck et al. 2001). The DPR is more sensitive to light rain rates and snowfall, which account for significant fractions of precipitation occurrences in middle and high latitudes (Kidd 2012). This will be a major improvement from the TRMM rain-sensing package, which focused primarily on heavy to moderate rain over tropical and subtropical oceans.

Through improved measurements of precipitation globally, the GPM mission will help to advance our understanding of Earth's water and energy cycle, improve forecasting of extreme events that cause natural hazards and disasters, and extend current capabilities in using accurate and timely information of precipitation to directly benefit society. GPM is also expected to improve weather and precipitation forecasts through assimilation of instantaneous precipitation information (Kidd 2012; Neeck et al. 2001).

Gravity Recovery and Climate Experiment

The Gravity Recovery and Climate Experiment (GRACE) mission is a joint partnership between U.S. National Atmospheric and Space Administration (NASA) and the Deutsche Zentrums für Luft- und Raumfahrt (DLR) in Germany. Launched in 2002, the mission maps the variations in the Earth's gravity fields by making accurate measurements of the distance between the two satellites, using GPS and a microwave ranging system. GRACE consists of two identical spacecrafts flying about 220 kilometers apart in a polar orbit 500 km above the Earth. This mission will acquire valuable information about the distribution and flow of mass within the Earth and its surroundings (Tapley 2004).

The gravity variations that GRACE will study include: changes due to surface and deep currents in the ocean; runoff and ground water storage on land masses; exchanges between ice sheets or glaciers and the oceans; and variations of mass within the Earth. Another goal of the mission is to create a better profile of the Earth's atmosphere. Additionally, GRACE

will monitor the mass and location of water as it moves around on the surface of the Earth, cycling between the land, oceans, and polar ice caps (Tapley 2004).

A recent study by Qiao et al. (2013) used GRACE water storage data and water table data from well logs to model the Lower Missouri River Basin with Soil and Water Assessment Tool (SWAT). They found that by coupling streamflow and GRACE data simultaneously, they could accurately predict the water balance, but that it caused improper partitioning of surface flow and baseflow. Another study, Li et al. (2012), modeled 18 basins in western and central Europe in the NASA Catchment land surface model using anomalies of terrestrial water storage observations from the GRACE satellite mission. Each basin was modeled over a 7-year period. GRACE driven models led to improved runoff estimates in 17 out of 18 hydrological basins, even in basins smaller than the effective resolution of GRACE.

2.4 Hydrologic Models

There are many types of hydrologic models developed as tools for predicting and forecasting water quantity and quality constituents. These models range in their conceptual structure from empirically based, lumped, distributed, to statistically based. The overall goal of all hydrologic models is to allow objective and quantitative decision-making for water quality and quantity management (Sivapalan 2003). A wide array of hydrological models are available for watershed simulation, several of these are freely available to the public. Commonly employed models are presented, including BASINS/HSPF (U.S. Environmental Protection Agency), WMS (U.S. Army Corps of Engineers), GSFLOW (U.S. Geological Survey), and VIC (University of Washington).

BASINS/HSPF

HSPF is a comprehensive and conceptual watershed-scale model developed and maintained by the U.S. Environmental Protection Agency that provides a continuous simulation of the streamflow, sediment and several water quality constituents on pervious land and impervious surfaces, in soil profiles, and within streams and well-mixed reservoirs (Bicknell et al. 2001; Kim et al. 2007). The model, which is adapted from the Stanford Watershed Model, consists of lumped parameters driven by rainfall and temperature data as well as land surface characteristics to simulate the contaminant runoff with in-stream water quality and sediment interactions. Even though HSPF is a lumped parameter model, it is considered moderately physically based and has the ability to divide a watershed into many hydrologically homogeneous land segment and simulate runoff for each segment independently (Wu et al. 2006). Figure 2.1 shows the model structure for the PERLND segment of the HSPF model, and Table 2.1 provides a description of the important hydrologic parameters used by HSPF.

Watershed Modeling System

The Watershed Modeling System (WMS) is a comprehensive hydrologic modeling environment developed by the U.S. Army Corps of Engineers for all phases of watershed hydrology and hydraulics. The modular design of the program enables the user to select modules in custom combinations, allowing the user to choose only those hydrologic modeling capabilities that are required. The software will dynamically link to these subsequent modules at run time, automatically adding additional modeling capability to the software.

The software supports hydrologic modeling with HEC-1 (HEC-HMS), TR-20, TR-55, Rational Method, NFF, MODRAT, and HSPF. Hydraulic models supported include HEC-RAS and CE QUAL W2. 2D integrated hydrology (including channel hydraulics and groundwater

interaction) can now be modeled with GSSHA. All of this in a GIS-based data processing framework will make the task of watershed modeling and mapping easier than ever before.

Ground- and Surface-Water Flow

The Ground- and Surface-water FLOW (GSFLOW) is a coupled hydrologic model developed by the U.S. Geological Survey (USGS) to simulate groundwater and surface water resources (Geological and Markstrom 2008). The model is based on the integration of the USGS Precipitation-Runoff Modeling System (PRMS) and the USGS Modular Groundwater Flow Model (MODFLOW - 2005). An important aspect of the model design is its ability to conserve water mass and to provide comprehensive water budgets. GSFLOW provides a modeling system for simulating runoff and infiltration in watersheds of varying ranges spatially and temporally.

Variable Infiltration Capacity

The Variable Infiltration Capacity (VIC; Liang et al. 1994) model is a large-scale, semi-distributed grid-based hydrologic model developed that solves for both water and energy balances. It was developed at the University of Washington and Princeton University and is based on the work of Xu Liang. VIC has been applied to many large river basins in the U.S. including the Mississippi River (Cherkauer et al. 1999).

2.5 Parameter Estimation Tools

All hydrologic models must be calibrated to establish the parameter values that provide the best predictions of watershed behavior. The methods presented here include HSPexp and PEST.

An important component of streamflow modeling is model calibration. In order to predict future forecasts in stream discharge, a model must be calibrated over a representative time period that represents the watersheds full, or near full, behavior. This was traditionally done manually by adjusting parameters using expert knowledge until an acceptable fit was achieved. The models ability to predict events can then be analyzed using an evaluation period outside of the calibration time period.

As models have become more robust and computational power has increased, it has become increasingly common to use some form of automatic calibration. A study by Kim et al. (2007) on the North River watershed in Virginia, compared calibrated methods using HSPexp version 2.4 and PEST and concluded that PEST provided a suitable alternative to manual calibration of river discharge.

There are several ways in which automatic calibration can be done, but they generally involve reducing the difference between observed and model simulated data and reducing the size of the parameter space. The closeness between simulated and observed datasets is measured by an objective function and parameters are adjusted by an iterative search procedure to find the optimal value of the objective function (Gupta 2006).

Calibration approaches are further broken down into global and local optimization algorithms. The issue with calibrating conceptual models to real observed data is that parameters are often simplified representations of reality and are not directly measureable. This leads to the issue of non-uniqueness of parameters, a condition Beven (1993) termed equifinality.

Typically, global optimization algorithms are considered more robust in finding the true parameter set for a given model condition, but are still subject to equifinality. The benefit of using a local optimization algorithm, specifically PEST, is that the computational time is significantly faster and the model-independent nature of the software makes it easy use. For this study, we used the localized parameter estimation software PEST that is nested in the HSPF framework.

It has also been suggested that a combination of goodness-of-fit metrics, at least one absolute error measure, bias, and other supporting information such as the means and standard deviations of observed and simulated flows are necessary for a good evaluation of model performance (Willmott 1981; Legates and Davis 1997; Legates and McCabe 1999; McCuen et al. 2006; Moriasi et al. 2007).

Hydrologic modeling studies commonly use statistical measures to evaluate the goodness-of-fit between the simulated and observed datasets, including the coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), Nash-Sutcliffe Efficiency (NSE; Nash and Sutcliffe 1970), and the modified Nash-Sutcliffe Efficiency (mNSE; Legates and McCabe 1999). These metrics can be sensitive to extreme values and can give a bias that limits the statistical efficiency (Legates and McCabe 1999; McCuen et al. 2006; Moriasi et al. 2007). Relative bias (R_b ; McCuen et al. 2006), percent bias (PBIAS; Moriasi et al. 2007), and ratio of RMSE to the standard deviation of observed data (RSR; Singh et al. 2005; Moriasi et al. 2007) are all methods to evaluate the statistical bias. One method for reducing the bias is to take the logarithm of the data.

HSPexp

HSPF comes equipped with the decision-support software Expert System for the Calibration of HSPF (HSPexp; Lumb et al. 1994). HSPexp software provides manual calibration guidance, suggesting parameter adjustments that sequentially address total volume, then low flows, storm flows, and finally seasonal flows using expert advice compiled from experienced modelers. HSPexp calculates percent errors of the model performance variables for each calibration run and provides guidance based on the values of those errors relative to predefined criteria. The modeler has the freedom to adjust the default values for model performance criteria based on the use of the model.

PEST

Parameter ESTimation (PEST) is a model-independent parameter estimation tool that reduces the weighted least squares between observed and simulated data. PEST uses a variation of the Gauss-Marquardt-Levenburg method for nonlinear parameter estimation, which greatly reduces calibration time for complex models and large datasets (Doherty 2001). The software uses a multi-objective function, defined as the difference between modeled and measured flow, to calibrate simulated flow to observed gauge flow data (Doherty 2001).

PEST is utilized by HSPF to automatically calibrate a hydrologic model by modifying streamflow parameter values within user defined limits using iterative runs. PEST uses the Gauss-Marquardt-Levenburg nonlinear parameter estimation method to optimize variable parameters during each iteration of the model (Doherty 2001). The software uses multiple objectives to calibrate simulated flow to observed gauge flow data, where the objectives are based various metrics related to differences between modeled and measured flows (Doherty 2001).

MCMC

Markov Chain Monte Carlo (MCMC) simulation is a method for determining the likelihood of a particular input dataset. It works by assuming a probability distribution for each uncertain characteristic and iteratively running a model with random values for each characteristic within that predefined probability distribution. The simulations are then used to construct a probability distribution for the model outputs.

This method is considered the most robust among modelers and is very computationally burdensome. MCMC is theoretical in nature and has become the preferred method of addressing uncertainty in complex hydrological modeling (Binley et al. 1991). It is subjective

in the selection of the probability distribution for the input variables and the total number of simulations generated.

GLUE

The Generalized Likelihood Uncertainty Estimation (GLUE) method uses Monte Carlo sampling to produce a series of model outputs. GLUE goes one step further and uses all of the outputs by weighting them based on their individual likelihoods and forming a cumulative distribution of predictions (Beven and Binley 1992).

2.6 Intercomparison Studies

Several intercomparison studies have been conducted on remote sensing products. Some of the more relevant studies are summarized below.

In a study by Kim et al. (2013), tropical precipitation characteristics were investigated using the TRMM 3-hourly estimates, and compared to results of five reanalyses products including MERRA. Precipitation characteristics were evaluated in terms of the mean, convectively coupled equatorial wave activity, frequency characteristics, diurnal cycle, and seasonality of regional precipitation variability associated with submonthly scale waves. Besides the positive mean bias in the reanalyses, a spectral analysis revealed that the reanalyses have overreddened spectra with persistent rainfall. MERRA had the most persistent rainfall of the reanalyses products. The low-frequency waves with the period longer than 3 days are relatively well represented in MERRA, but all the reanalyses have significant deficiencies in representing convectively coupled equatorial waves and variability in the high-frequency range.

Khan et al. (2011) integrated MODIS and ASTER data with TRMM 3B42 Real Time precipitation data as inputs for the Coupled Routing and Excess Storage (CREST) dis-

tributed hydrologic model to characterize the spatial extent of flooding and associated hazards over sparsely gauged or ungauged basins. CREST was used to model the Nzoia basin, a subbasin of Lake Victoria in Africa. They conclude that the application is not only feasible due to the public availability of data in remote or ungauged basins, but that models driven with remotely sensed data can produce sufficient accuracy in predicting spatial flood extents.

Shepherd et al. (in print) examined seasonal bias of TRMM MPA-based and MERRA rainfall data on daily and sub-daily scale in the Southeastern US. They found that over all seasons TRMM MPA correlates more highly with the Global Precipitation Climatology Centre (GPCC) precipitation dataset than MERRA on a monthly scale. Additionally, they found that TRMM MPA tends to overestimate light precipitation relative to the multi-gauge average on a daily scale.

Gourley et al. (2011) conducted a study comparing the predictive abilities for NEXRAD, ground station, TRMM (TMPA), and PERSIANN-CCS precipitation products in a hydrologic model. They modeled the Ft. Cobb watershed in Oklahoma, a USDA-ARS research watershed that contained a high-density Micronet of ARS ground stations. Using the Micronet as reference precipitation, they found that NEXRAD stage IV outperformed all remote products and ground stations and was only slightly worse than the Micronet reference.

Table 2.1: HSPF parameter names, descriptions, units, and expected ranges.

Parameter	Description	Units	Min	Max
LZSN	Lower zone nominal soil moisture storage	inches	2	15
INFILT	Index to infiltration capacity	in/hr	0.001	0.5
AGWRCTRANS	Base groundwater recession (transformed)	none	-	-
DEEPFR	Fraction of GW in flow to deep recharge	none	0	0.5
BASETP	Fraction of remaining ET from baseflow	none	0	0.2
AGWETP	Fraction of remaining ET from active GW	none	0	0.2
CEPSC	Interception storage capacity	inches	0.01	0.04
UZSN	Upper zone nominal soil moisture storage	inches	0.05	2
INTFW	Interflow flow parameter	none	1	10
IRC	Interflow recession parameter	none	0.3	0.85

Source: Technical Note #6, USEPA, 2000.

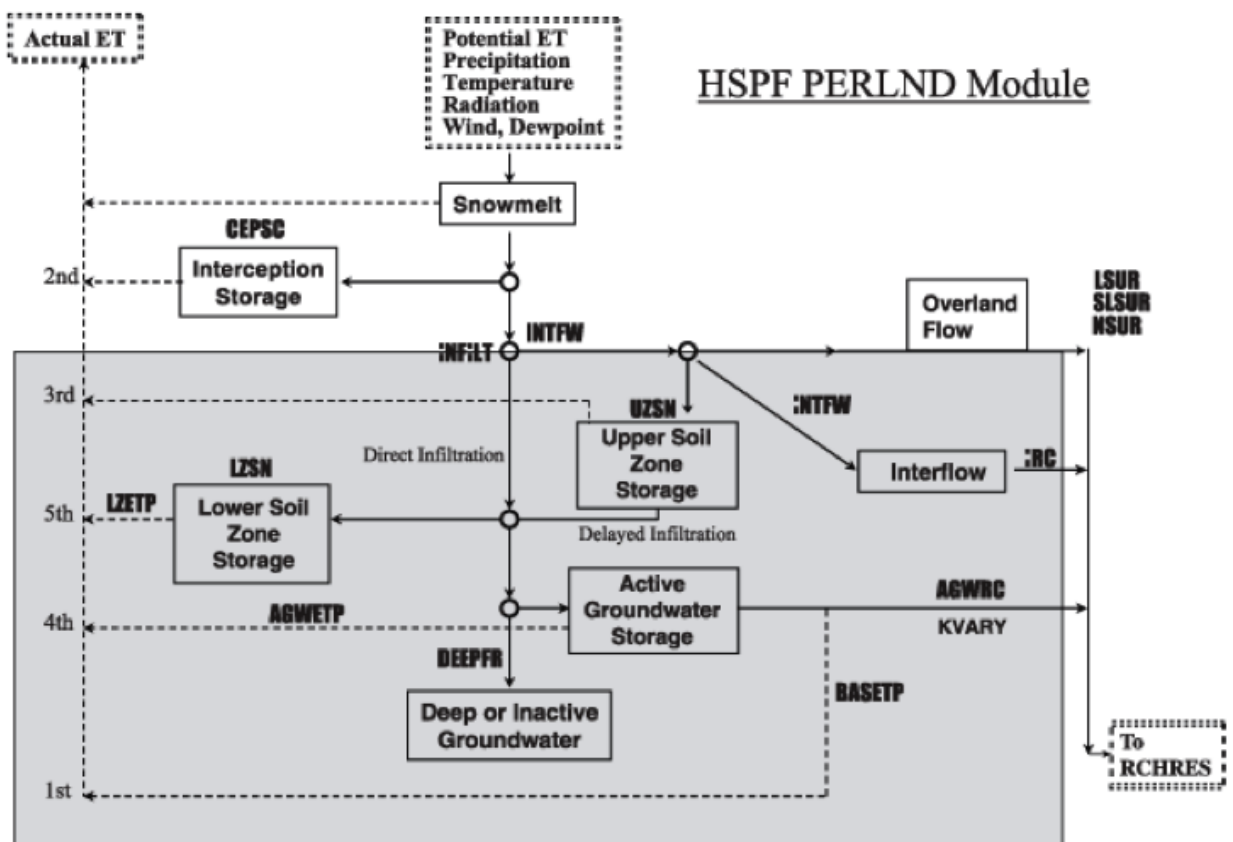


Figure 2.1: HSPF model parameters related to pervious land use segment (PERLND).

Source: <http://pubs.usgs.gov/sir/2005/5099/>

Chapter 3

Methods

This chapter summarizes the hydrologic modeling approach used in this thesis. It starts with a summary of the study area, followed by a summary of the data sources, model input specification, and model calibration and evaluation.

3.1 Study Area

Six watersheds were chosen within the Southeastern Coastal Plain and Piedmont Provinces. Three nested watersheds were selected on the Choctawhatchee¹ River (named (a), (b), and (c)), along with one site each on the Savannah River (Clyo), Neuse River, and Ogeechee River (Figures 3.1 to 3.6).

The selected watersheds vary in size, land cover, and percentage of area within each physiographic province (Tables 3.1 and 3.2). All selected watersheds have relatively low relief. Forested land cover ranges from 30 to 50 percent and urbanized area is less than 20 percent for all sites. Karst regions were avoided due to the unusual hydrologic behaviour of these landscapes.

¹Pronounced “CHOCK-tu-HAT-chee”

Precipitation in the selected watersheds ranges from 40-60 inches per year based on NOAA's 30-year (1981-2011) normals for ground-based meteorological stations used in modeling (Table 3.3). Three of the sites contain 11 years of streamflow and ground-based meteorological data, and two others contain more than six years of data. Data from each site were divided into calibration and evaluation periods to further examine the predictive capabilities of the scenarios.

3.2 Model

HSPF, nested in EPA's BASINS 4.0, was used to model each watershed in this study. The supplemental programs WDMUtil and GenScn were used to prepare climatological inputs and outflow predictions, respectively. Watersheds were delineated using the Automatic Watershed Delineation Tool in BASINS using the outflow gauge point, pre-generated stream reach file, and an elevation model.

3.3 Data Sources

Two general categories of information are needed to predict discharge in rivers; the meteorological inputs (such as precipitation and evapotranspiration), and landscape features (such as topography, land use, and land cover). These inputs have historically been collected using ground-based approaches. For remote, data-poor areas, however, these ground-based data may be difficult to acquire. This study used remotely sensed data that can be collected on a near global scale.

This study uses daily average data for all time series inputs and outputs. While this reduces the amount of total observations, it allowed for a fair comparison against coarser

datasets. Watersheds were modeled using English units and were converted to metric units for publication.

Meteorological Inputs

All hydrologic models use precipitation and evapotranspiration data to account for gains and losses to the hydrologic system. Conventionally, the data are obtained from ground-based locations, which are generally located in developed areas such as cities. Data from mountainous and remote areas are rarely collected, and often difficult to acquire even if they have been collected.

Ground-based meteorological data were obtained from NOAA's National Climatic Data Center (NCDC) through BASINS (until 2006) and through University of Georgia Extension Agricultural Climatologist Pam Knox. This is the traditional input for watershed modeling in BASINS/HSPF so the meteorological station shapefile can be automatically generated and data in model-ready format can be downloaded directly to the HSPF wdm file. Constituents are in inches and potential evapotranspiration (PEVT) is calculated using the Hamon Method. For more information on how ground meteorological data is prepared, refer to the BASINS 3.0 Manual (USEPA 2001).

Precipitation and potential evapotranspiration datasets were obtained from MERRA². Data is available from 1979 - near real-time present. MERRA data offers global coverage with six-hourly, three-dimensional atmospheric analyses and surface data fields at 1/2° x 2/3° spatial resolution. For details on how MERRA datasets are assimilated and calculated, refer to Rienecker et al. (2011). The second source of data is from the Tropical Rainfall Measuring Mission (TRMM) satellite³.

²<http://disc.sci.gsfc.nasa.gov/daac-bin/DataHoldings.pl>

³http://trmm.gsfc.nasa.gov/data_dir/data.html

TRMM and MERRA data was further extracted by station and compiled for each watershed matching its available observed flow time period. Software tools for accessing, subsetting, and formatting the necessary data sets were developed to allow the satellite and global re-analysis data to be used for the BASINS/HSPF modeling system. The necessary software was developed using Interactive Data Language (IDL), which provides the necessary libraries for reading both scientific data formats (e.g., netCDF and HDF) as well as ESRI shapefiles. IDL required a software license to develop the code, but executable versions of the software can be distributed using the freely available IDL virtual machine, which is available for most operating systems. Data was then aggregated to average daily values in inches.

The length of TRMM and MERRA grids vary depending on the latitude of the study site. The length of one degree of longitude is equal to cosine (latitude) times the length of degree (in miles) at the equator. Using Atlanta, GA (latitude of 33.7550°), as a relative point for the study sites, the distance for one degree is approximately 92.6 km in longitude and 111.3 km in latitude, ignoring polar flattening.

Spatial Information

In addition to meteorological input data, HSPF requires land-surface conditions and topography for determining drainage basins and other hydrologically relevant factors. These data are also essential for model calibration and evaluation. BASINS contains all needed surface input datasets for modeling in the United States.

Topographic relief was obtained using the USGS National Elevation Dataset (NED) based on 30-meter grid cells. Each watershed subbasins were delineated using a stream reach file (1:500k) provided by USEPA in the BASINS setup and a network delineation threshold area of 52 km² with the exception of the Clyo and two of the Choctawhatchee(Choctawhatchee(b) and Choctawhatchee(c)) watersheds, which used thresholds of 104 km² due to processing constraints. These sites also used resampled NED grids with 60-m resolution.

Land use was obtained from the 2001 National Land Cover Database (NCLD). The 2001 NLCD is a 16-class land cover classification scheme with a 30-m spatial resolution and is available across the conterminous United States (Homer et al. 2007).

Observed streamflow for watershed outlets were obtained from USGS gauge stations. Data were aggregated to average daily streamflow in cubic feet per second (cfs). Sites were selected that contained continuous data over the selected time period with no more than three consecutive days missing. Averages of the dates before and after were used for missing days.

For sites that contain reservoirs (Clyo), a pour point was added to the stream segment of the model where the regulated flow was released. This data was obtained through the USACE website for Clarks Hill/Thurmond dam. Data was input into the corresponding stream segment as daily average flow in cfs.

3.4 Model Inputs

Three HSPF models were created for each watershed. These models are identical except for the input sources used: 1) ground-based meteorological data only 2) MERRA remotely-sensed meteorological data only 3) MERRA (potential evapotranspiration) and TRMM (precipitation) data. TRMM and MERRA meteorological data was downloaded for each of the selected watersheds using an IDL script from the sites mentioned above. Grids for each were converted to points based on their centroids and used as point stations for processing purposes.

Precipitation Input Methods

Additionally, each of these models were compared to three methods of input into the HSPF model. Each combination was input using three different spatial sampling sizes: 1) a single

grid/station closest to the centroid of the watershed 2) multiple grids/stations covering the extent of the watershed boundaries 3) a single grid/station comprised of the weighted average of all other surrounding station/grid data within the watershed boundaries. This gives a total of nine simulations for each selected site. All models used daily data, which was aggregated from its original hourly format.

Single Grid Nearest Neighbor Model. This method uses the closest meteorological station to the centroid of the watershed being modeled. The centroid is calculated for each watershed in ArcMap. The method is the same for all three inputs, but ground-based meteorological stations are sometimes much further distances, due to limited sites with long periods of continuous data for both precipitation and potential evapotranspiration.

Multiple Grid Segmented Model. Models created using this method were segmented based on proximity to individual meteorological or virtual stations. Subsets of subbasins were created and driven by different precipitation and potential evapotranspiration inputs. Due to the limitations of PEST, a maximum of five segments was set so that optimization could be achieved. This limitation is based on the ratio of observations to parameters to be optimized. As the number of parameters increase and the number of observations stay the same, the optimization problem becomes increasingly unstable.

Thiessen polygons were created for TRMM and MERRA centroid grids over each watershed. Five stations were selected with the largest polygon areas for TRMM stations. MERRA stations were selected in the same process, but due to the coarser coverage resolution, less than five stations were selected for some models. Also, in small watersheds, less than five TRMM stations may have been used.

Because TRMM stations have a denser network than MERRA stations, MERRA potential evapotranspiration was assigned based on proximity to the TRMM station. The TRMM segments consist of the selected TRMM precipitation inputs and the selected MERRA po-

tential evapotranspiration inputs. The MERRA-segmented model contains the selected MERRA precipitation and potential evapotranspiration inputs.

Single Grid Merged Model. This method was slightly different for ground based and remotely sensed inputs. Ground-based data is not uniform in coverage both spatially and temporally. Therefore the ground stations were analyzed for each individual watershed and stations were selected that contained a sufficient length of continuous data (hourly).

TRMM and MERRA data contain uniform temporal and spatial data so there selection was the same for each site. Thiessen polygons were created for TRMM and MERRA centroid grids over each watershed. From these original polygons, grids that contained less than three percent of the total area were removed from selection and another set of Thiessen polygons were created with the remaining grids. The fraction of the total area covered by each grid was recorded and used in a weighted average merge of all the stations for a particular product and watershed. The TRMM merged model consists of the merged TRMM precipitation input and the merged MERRA potential evapotranspiration input. The MERRA merged model contains the merged MERRA precipitation and potential evapotranspiration.

3.5 Parameter Estimation

PEST was used to calibrate each of the nine scenarios for all six Piedmont/Coastal Plains watersheds. The default setting in HSPFs PEST function was used to obtain the lowest objection function for each scenario over the calibration period. The calibration involved 30 iterations of the multi-objective function to determine the best parameter set for the given time span and climatological inputs.

HSPF was run again using the evaluation time period and the calibrated parameter set for each scenario. The output simulations for both calibration and evaluation periods were

recorded as hourly average streamflow in units of cfs. These outputs were used to assess the predictive ability of each climatological product input.

3.6 Model Calibration and Evaluation

BASINS 4.1, HSPF, and PEST software were used to calculate parameters and simulate flow for each watershed scenario. A warm-up period of one year was used to remove the initial transient that is caused by assumptions about the initial state of the watershed variables. The initial year was removed from the data for both calibration and evaluation periods prior to all analyses.

Baseflow Separation

To examine how methods performed over different flows, a program was developed for this study to separate model observations and simulations into baseflow and stormflow. The simulation datasets were then analyzed independently for each calibration and evaluation period as average daily streamflow, stormflow, and baseflow in both linear and log-transformed flow for each of the models and model scenarios for a more robust comparison.

For stormflow, if either simulated or observed contained a zero, both values were removed from the vectors. This was done for both linear and log-transformed flow analysis, although only log-transformed flow presented a problem. Baseflow and stormflow was calculated using the Eckhardt digital filter. The filter parameter (α) was computed from selected recession by ordinary least squares regression, with an offset of three and ranging values of the length of recession (Table 3.4). For all model scenarios, the BFI_{max} and omega were set to 0.4 and 0.5 as suggested by Eckhardt (2005).

Metrics

Each hydrologic model was evaluated using five statistical measures, shown in equations 3.1 - 3.5. The metrics include the coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), Nash-Sutcliffe Efficiency (NSE; Nash and Sutcliffe 1970), and the modified Nash-Sutcliffe Efficiency (mNSE; Legates and McCabe 1999). The statistics were computed for each scenario using BASflow Separation Tool (BASSET).

$$R^2 = \left(\frac{\sum_{i=1}^n (Q_o^t - \overline{Q_o}) (Q_m^t - \overline{Q_m})}{\sqrt{\sum_{i=1}^n (Q_o^t - \overline{Q_o})^2} \sqrt{\sum_{i=1}^n (Q_m^t - \overline{Q_m})^2}} \right)^2 \quad (3.1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Q_m^t - Q_o^t)^2} \quad (3.2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |Q_m^t - Q_o^t| \quad (3.3)$$

$$NSE = 1 - \frac{\sum_{t=1}^T (Q_o^t - Q_m^t)^2}{\sum_{t=1}^T (Q_o^t - \overline{Q_o})^2} \quad (3.4)$$

$$mNSE = 1 - \frac{\sum_{t=1}^T |Q_o^t - Q_m^t|^2}{\sum_{t=1}^T |Q_o^t - \overline{Q_o}|^2} \quad (3.5)$$

where Q_o^t is observed discharge at time t, Q_m^t is simulated discharge at time t, $\overline{Q_o}$ is the mean of the observed data, and $\overline{Q_m}$ is mean of the simulated data.

Additional analysis was done on the overall model simulations for both the calibration and evaluation periods. Relative bias (R_b ; McCuen et al. 2006), percent bias (PBIAS; Moriasi et al. 2007), and ratio of RMSE to the standard deviation of observed data (RSR; Singh et al. 2005; Moriasi et al. 2007) were calculated for each scenario (Equations 3.6 - 3.9). The means and standard deviations of observed and simulated flows were also recorded.

$$\bar{e} = \frac{1}{n} \sum_{i=1}^n (Q_m^t - Q_o^t) \quad (3.6)$$

$$R_b = \frac{\bar{e}}{\bar{Q}_o} \quad (3.7)$$

$$PBIAS = \frac{\frac{1}{n} \sum_{i=1}^n (Q_o^t - Q_m^t)}{\bar{Q}_o} \times 100 \quad (3.8)$$

$$RSR = \frac{RMSE}{STDEV_{obs}} \quad (3.9)$$

To compare satellite meteorological inputs performed as a replacement for ground-based meteorologic inputs, a ratio of the residual standard errors was taken between models. The residual standard error of the ground based prediction (e_g) is defined by Equation 3.10.

$$e_g = SE(Q_g/Q_o) \quad (3.10)$$

where e_g is the residual standard error of the ground-based prediction, equal to the standard error of the ratio between the predicted streamflow, Q_g , using ground-based information and the observed streamflow, Q_o . e_g will be positive (always), equal to zero for the case of a perfect fit. The standard error is just the square root of the variance of the ratios:

$$SE(x) = \sqrt{Var(x)} \quad (3.11)$$

where the variance is calculated using:

$$Var(x) = \sum (x - \mu)^2 / (n - 1) \quad (3.12)$$

where $\mu = E(x)$ is the mean, or expected value of x . If the estimator is unbiased, then the expected value of the ratios is 1, so you could just put $\mu = 1$ in here. This was repeated for the other inputs:

$$e_m = SE(Q_e/Q_o) \quad (3.13)$$

and

$$e_t = SE(Q_e/Q_o) \quad (3.14)$$

and the ratio between each of the other metrics and the ground-based metric were compared:

$$\beta_m = e_m/e_g \tag{3.15}$$

$$\beta_t = e_t/e_g \tag{3.16}$$

If $\beta > 1$, then it performs more poorly, while $\beta < 1$ indicates that it performs better than the ground-based approach. Table 4.2 show the ratios of the six watershed models.

Table 3.1: Watershed characteristics for six modeled watersheds in the Southeastern US.

USGS ID	Model Name	Period (days)		Physiographic Province (%)	
		Calibration	Evaluation	Coastal Plain	Piedmont
02361000	Choctawhatchee(a)	1,580	1,644	100	0
02365500	Choctawhatchee(b)	2,556	1,825	100	0
02366500	Choctawhatchee(c)	1,611	1,674	100	0
02198500	Clyo	2,190	2,191	73	27
02089000	Neuse	2,495	1,886	46	54
02201230	Ogeechee	1,309	1,459	75	25

Table 3.2: USGS gaging stations used for watershed simulations.

USGS ID	Site Name	Latitude (North)	Longitude (East)	Hydrologic Unit Code	Area (km ²)
02361000	ChoctawhatcheeRiver nr Newton AL	31°20'34"	85°36'38"	03140201	2,315
02366500	ChoctawhatcheeRiver nr Bruce FL	30°27'03"	85°53'54"	03140203	9,125
02365500	ChoctawhatcheeRiver at Caryville, FL	30°46'32"	85°49'40"	03140203	11,406
02198500	Savannah River nr Clyo GA	32°31'41"	81°16'08"	03060109	9,127
02089000	Neuse River nr Goldsboro NC	35°20'15"	77°59'51"	03020202	6,084
02201230	Ogeechee River at Midville GA	32°48'52"	82°14'07"	03060201	3,419

Table 3.3: NOAA 30-year (1981-2011) meteorological data for ground-based stations.

Ground Station		Precipitation (in)	Temperature ($^{\circ}F$)		
Name	Number		Min	Mean	Max
Clayton	AL011725	–	50.1	63.2	76.4
Geneva No 2	AL013251	59.11	53.1	65.7	78.2
Headland	AL013761	53.77	55.3	66.4	77.6
Chipley	FL081544	59.08	55.8	67.7	79.6
De Funiak Springs	FL082220	63.71	55.6	66.9	78.2
Augusta Bush Field AP	GA090495	43.57	51.0	63.9	76.9
Louisville 1 E	GA095314	45.06	52.0	64.0	76.0
Midville Exp Sta	GA095863	44.60	52.8	64.4	75.9
Sandersville	GA097777	46.97	51.5	63.5	75.4
Siloam 3 N	GA098064	46.08	49.8	62.1	74.4
Warrenton	GA099141	–	50.1	62.0	74.0
Waynesboro 2 S	GA099194	47.80	52.2	64.2	76.1
Clayton WTP	NC311820	46.42	47.9	59.6	71.3
Durham	NC312515	47.81	46.7	57.9	69.1
Raleigh State Univ	NC317079	46.02	49.5	60.6	71.6
Roxboro 7 ESE	NC317516	45.37	44.1	57.0	69.8
Smithfield	NC317994	47.75	48.7	59.8	70.9
Allendale 2 NW	SC380126	46.33	51.1	64.0	76.8
Johnston 4 SW	SC384607	46.91	49.6	61.3	73.0

Table 3.4: Baseflow separation settings for streamflow simulation models.

(For all models, regression method is ordinary least squares, offset is three, minimum length is seven, Filter is Eckhardt, BFImax is 0.4, and omega is 0.5.)

	HSPF Watershed Model					
	Neuse	Ogeechee	Clyo	Choctawhatchee		
				(a)	(b)	(c)
Number	153	86	20	100	93	224
Slope	0.872	0.934	0.978	0.958	0.808	0.922
Intercept	52.27	7.18	50.65	-2	419.72	132.67

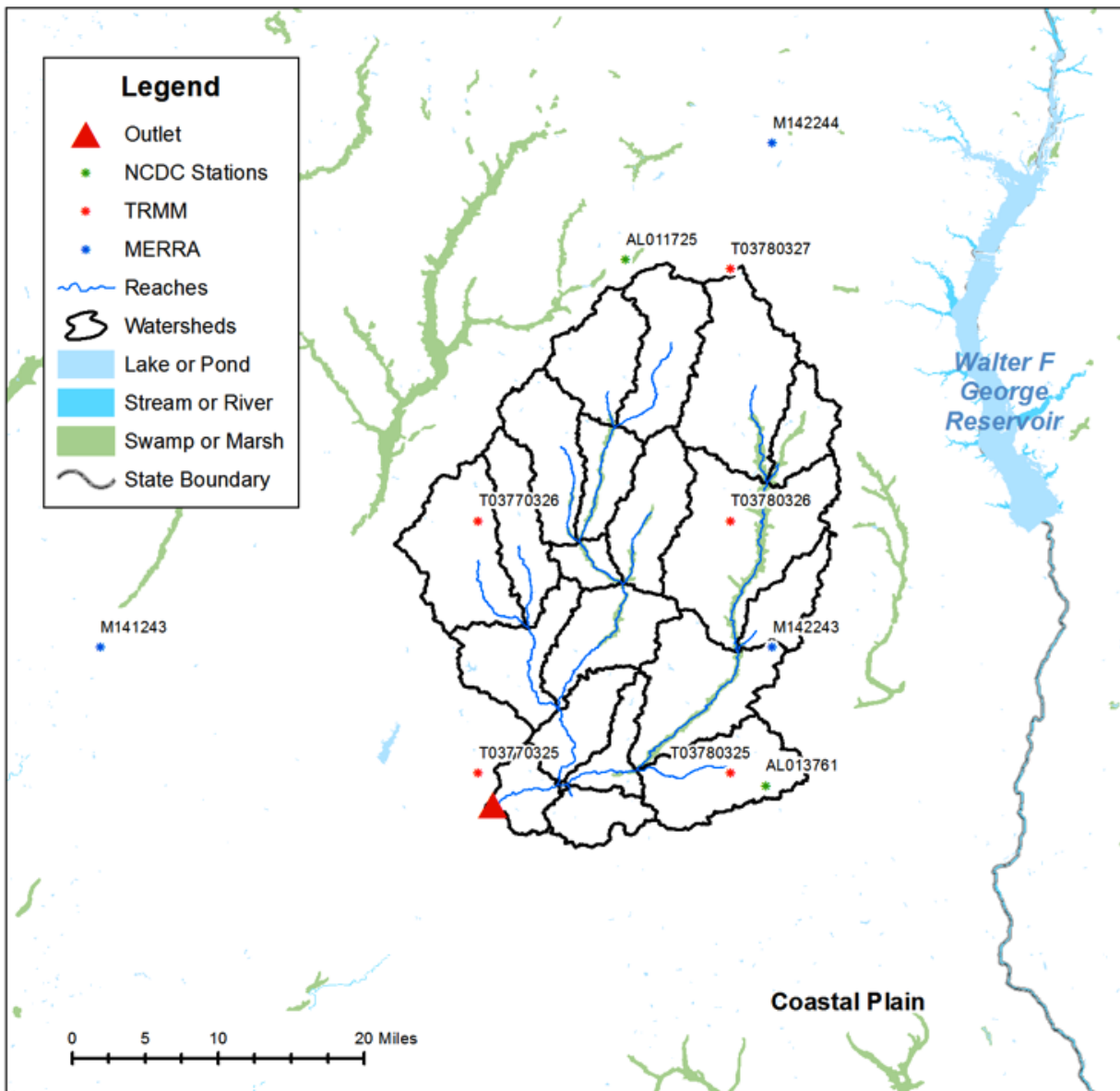


Figure 3.1: Basemap of Choctawhatchee(a) watershed.

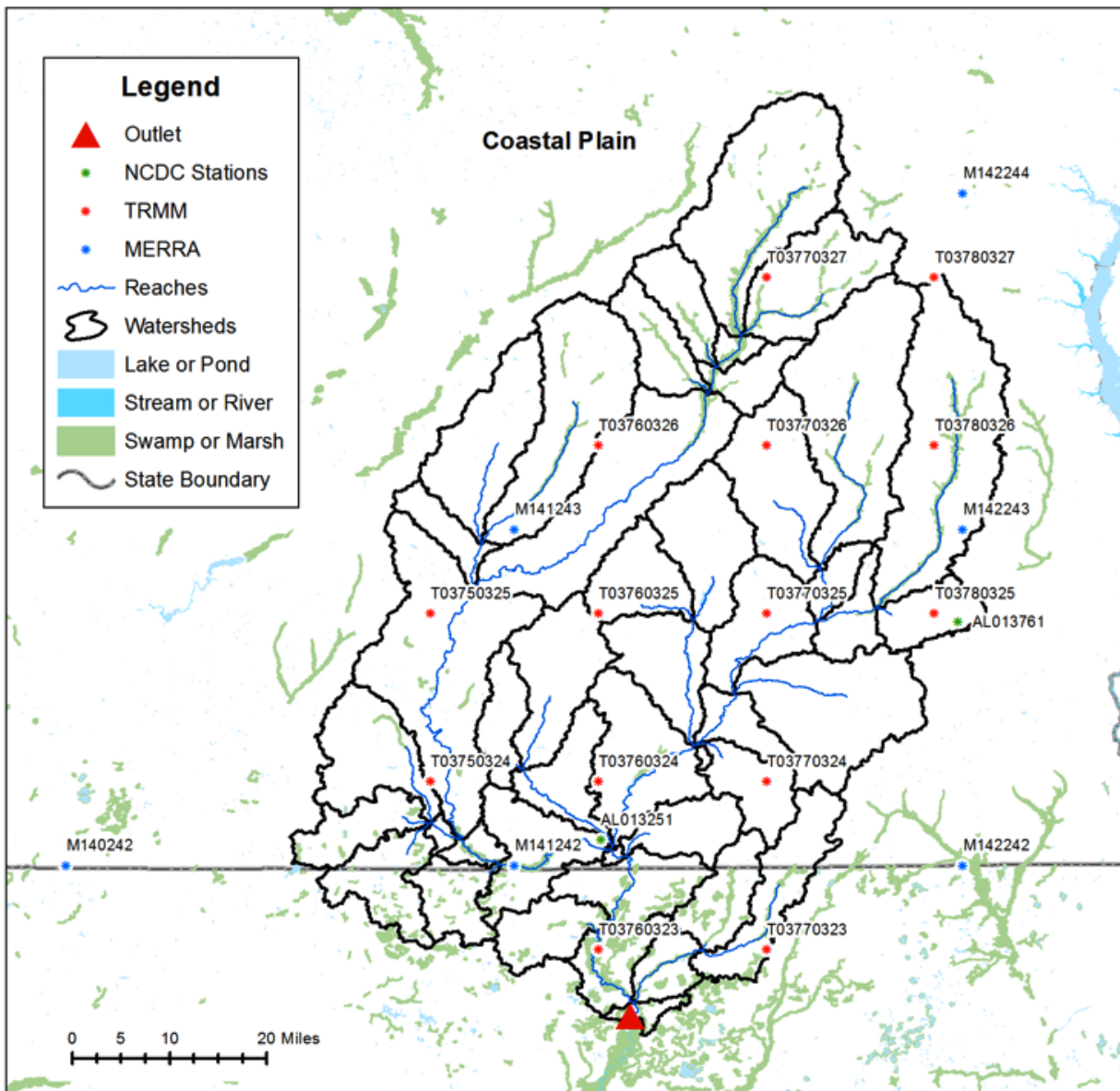


Figure 3.2: Basemap of Choctawhatchee(b) watershed.

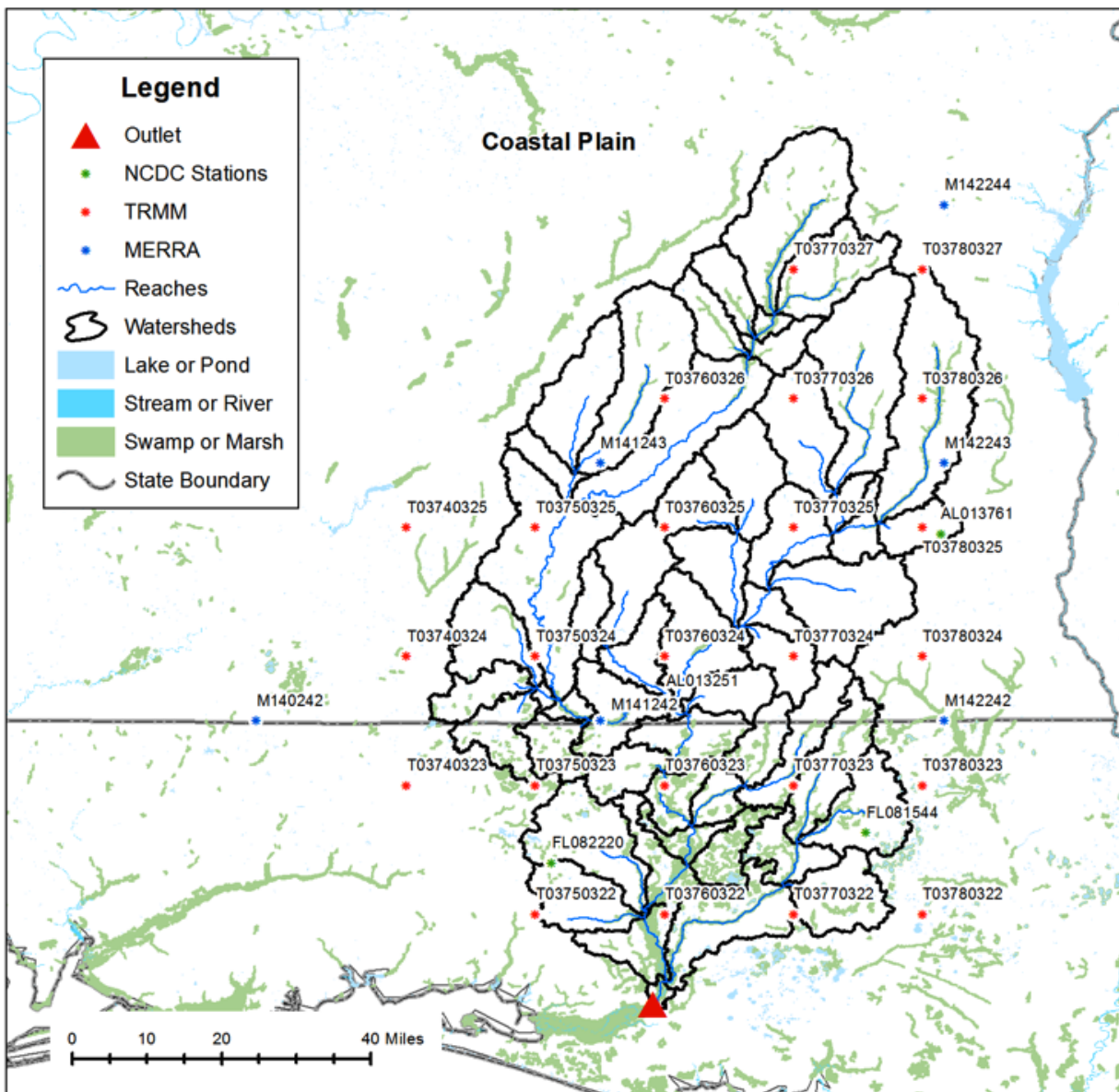


Figure 3.3: Basemap of Choctawhatchee(c) watershed.

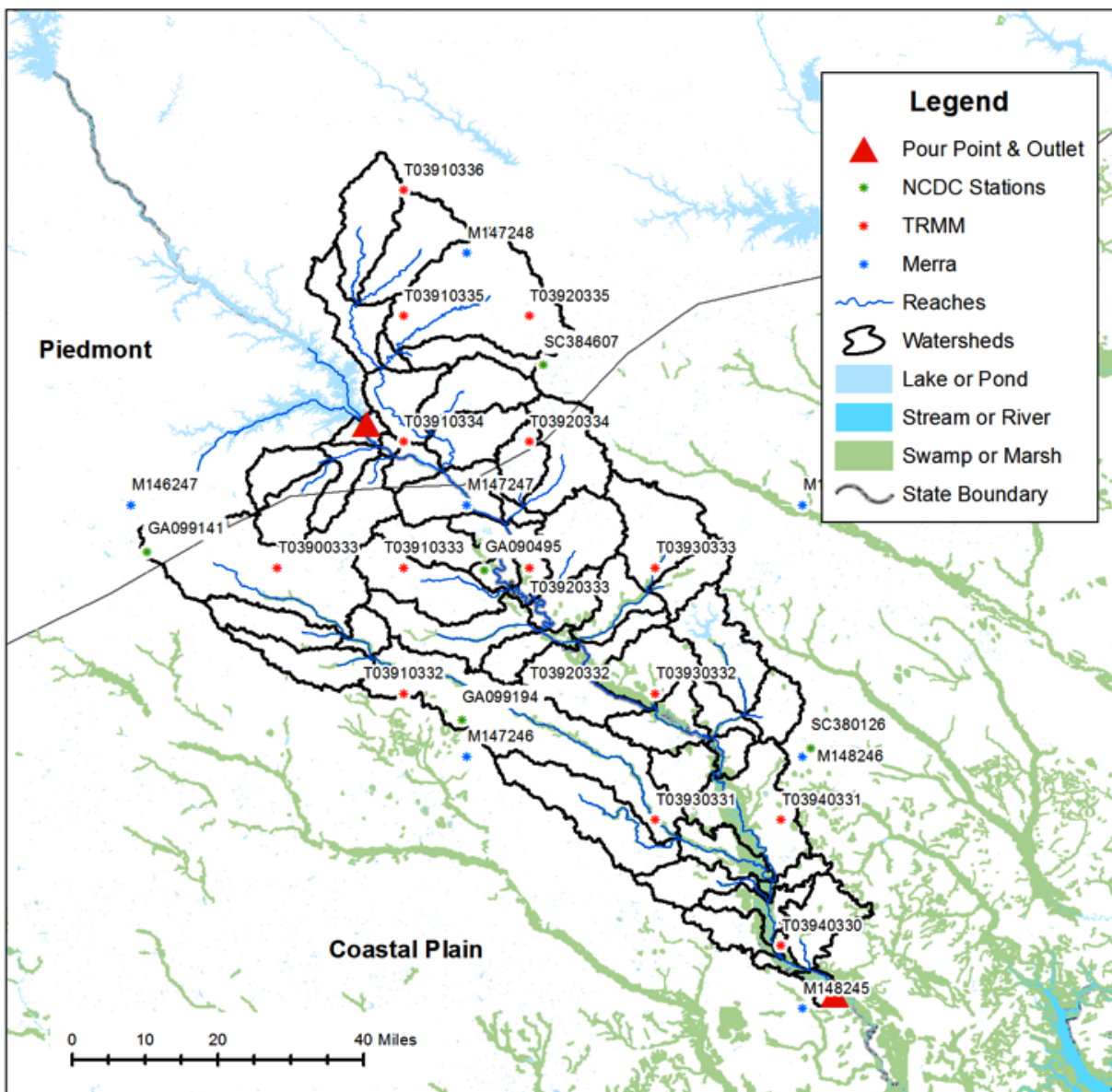


Figure 3.4: Basemap of Clio watershed.

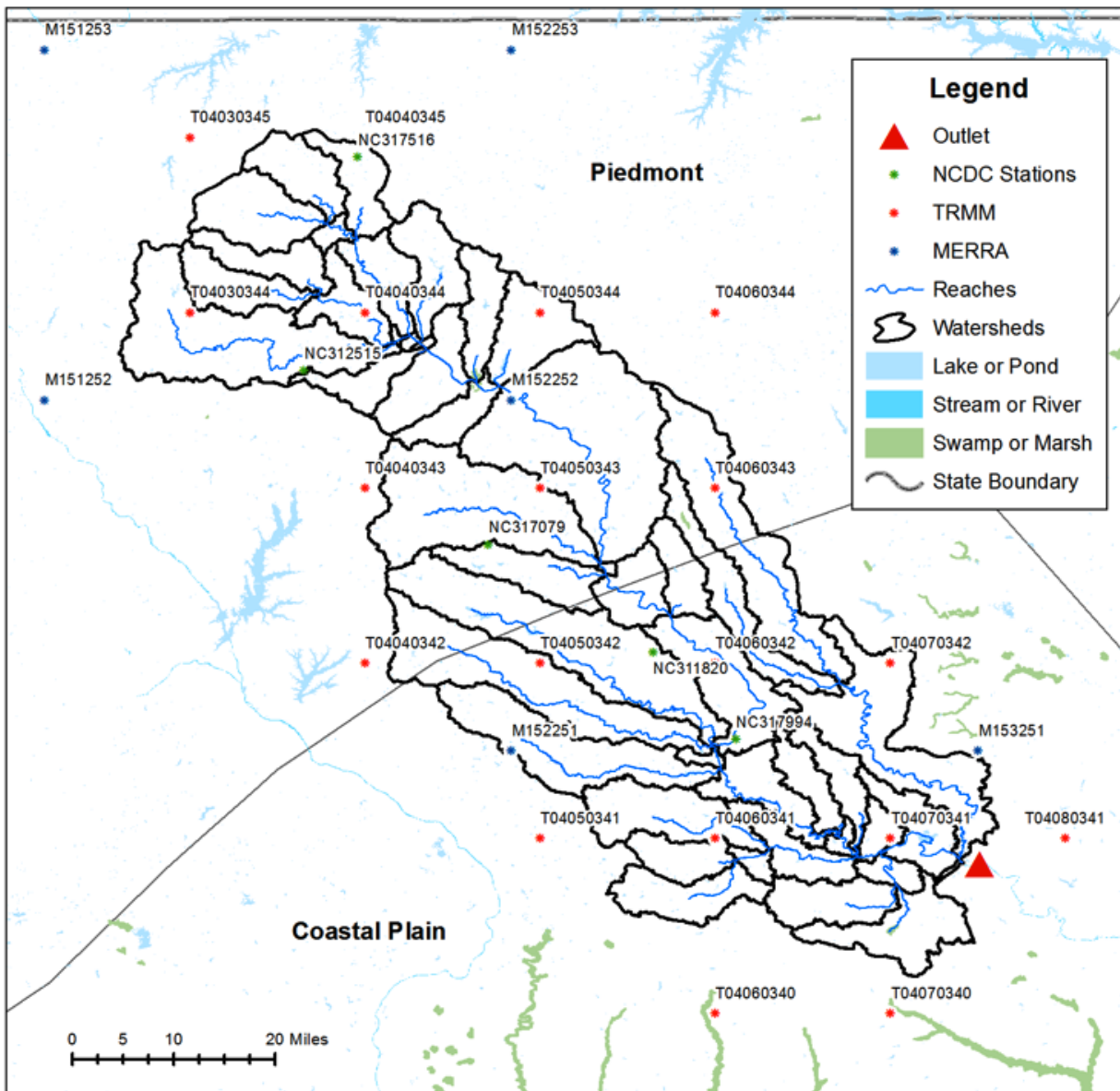


Figure 3.5: Basemap of Neuse watershed.

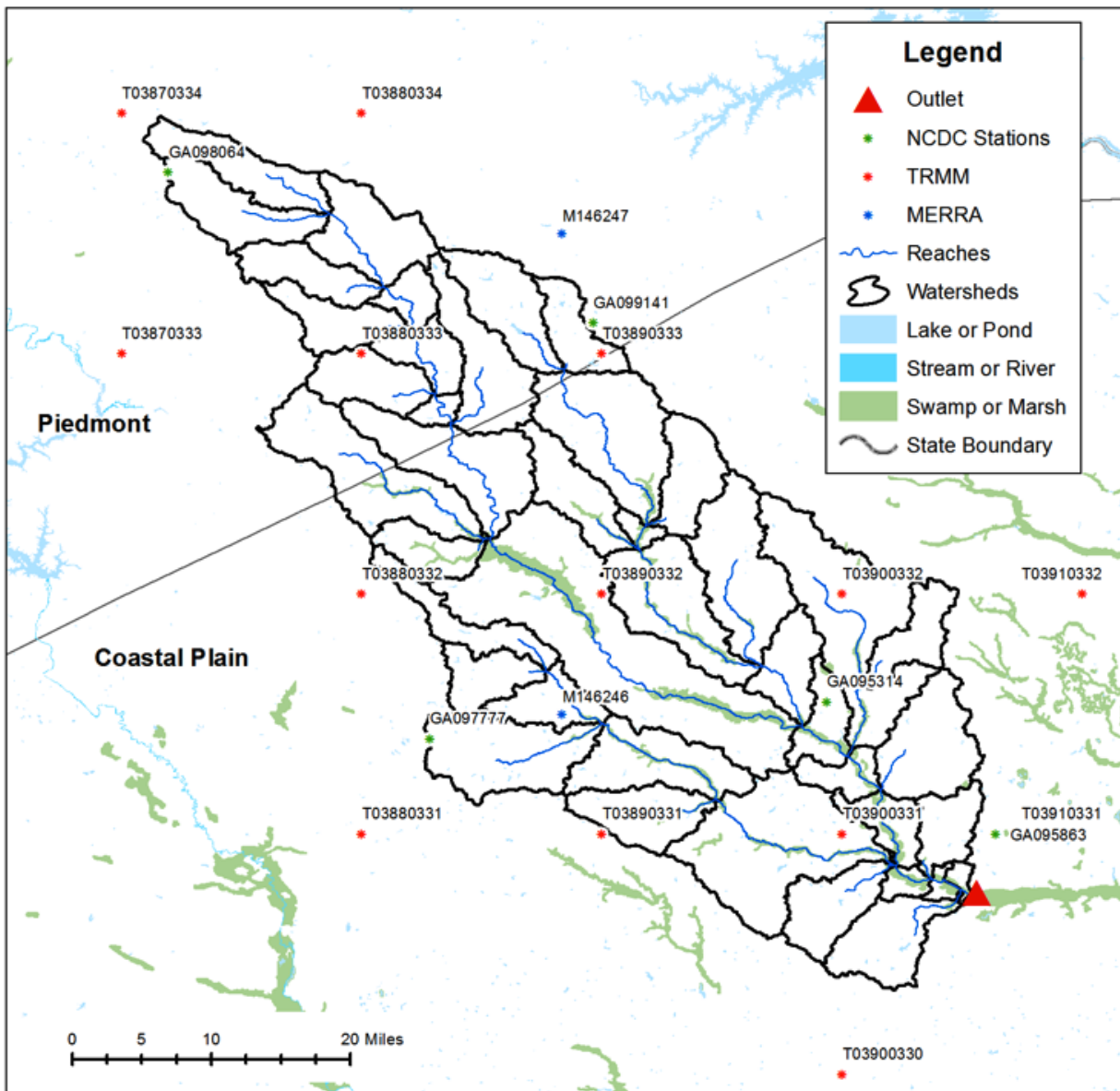


Figure 3.6: Basemap of Ogeechee watershed.

Chapter 4

Results

We now present the results of the analyses described in the previous section. Because the goal of this thesis is to evaluate the accuracy of a hydrologic model (BASINS - HSPF), we use a range of uncertainty analyses to compare alternative model predictions with observed streamflow in six watersheds within the Southeastern Coastal Plains.

4.1 Time Series Plots

One technique for evaluating the accuracy of hydrologic models is to perform a visual inspection of how well the model predictions fit the observed data. Hydrographs for selected stations (Choctawhatchee(a) and Choctawhatchee(b)) and periods are presented as Figures 4.1 to 4.8. Each figure presents hydrographs using linear, or untransformed, discharge, as well as log-transformed discharge (top and bottom, respectively).

Note that low flows are more apparent on the log-transformed scales, while higher flows are more visible on the untransformed scale. The figures show the observed data, along with predictions based on TRMM and MERRA atmospheric data sources using segmented

and watershed averaged input methods. It is clear that fits of low and high flows can be qualitatively judged in terms of magnitude and timing of observed and predicted values.

4.2 Q-Q Plots

The so-called Q-Q (or Quantile-Quantile) plots are another method for qualitatively comparing observed with predicted streamflow. Q-Q plots were generated by ranking and sorting average daily streamflow for simulated and observed data. The two datasets were plotted against each other with observed data on the x-axis.

Figures 4.9 to 4.10 and Figures 4.11 to 4.12 show the Q-Q plots for the Choctawhatchee(a) and Choctawhatchee(b) watersheds, respectively, for the areally weighted and segmented input methods.

4.3 Double Mass Curves

Mass curve plots are helpful in identifying systematic bias in the precipitation datasets. The idea of the double mass curve is based on the fact that a plot of the two cumulative quantities during the same period exhibits a straight line so long as the proportionality between the two remains unchanged, and the slope of the line represents the proportionality (Searcy et al. 1960).

Double mass curve plots were generated for the Choct (a) and Choct (b) nearest neighbor and weighted average scenarios (Figures 4.13 and 4.14). These plots used cumulative rainfall (inches) on the horizontal axis versus cumulative streamflow at the watershed outlet on the vertical axis. Summaries of the regression lines of each plot can be seen in Table 4.3.

4.4 Statistical Measures

A more quantitative approach for assessing model performance is to use statistical measures. Eight statistical measures are used to compare model predictions with observed data; the coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), Nash-Sutcliffe Efficiency (NSE), modified Nash-Sutcliffe Efficiency (mNSE), relative bias (BIAS), percent bias (PBIAS), and the ratio of the root mean squared error to the data standard deviation (RSR).

The effect of watershed size is evaluated using both nested watersheds (i.e., basins with multiple streamflow gaging sites such that each watershed grows in size with downstream distance), and neighboring watersheds (i.e., basins from adjacent drainages that have similar land uses).

To improve model accuracy, we considered three sources for atmospheric (precipitation and evaporation) data, including ground-based observations, TRMM satellite estimates, and MERRA (re-analysis) inputs. Each of the alternative sources were aggregated prior to hydrologic model input using either a weighted average, segmented, or nearest neighbor technique.

We also compare model performance using two approaches:

- *Model Calibration Period.* This approach used a 50- to 80-month period of meteorologic and streamflow data. Model predictions were optimized by allowing parameter values to be adjusted for each watershed.
- *Model Evaluation Period.* This approach used an independent 50- to 70-month period of data along with model parameters determined during the calibration period.

Table 4.1 presents the mean and standard deviations for the observed data over 30-year period (when available), as well as for the calibration and evaluation periods. Table 4.2 presents the residual standard error ratios for:

- *Six Watersheds.* Choctawhatchee(a), Choctawhatchee(b), Choctawhatchee(c), Cloyo, Neuse, Ogeechee
- *One Flow Condition.* All flows
- *One Streamflow Variable.* Untransformed,
- *Two Periods.* Model calibration, Model evaluation
- *Two Atmospheric Input Sources.* TRMM, MERRA
- *Three Input Methods.* Nearest neighbor, Segmented, Weighted average

Tables 4.12 - 4.17 present a series of six tables that summarize the mean, standard deviation, and three of the eight model performance measures (R_b , PBIAS, and RSR) for:

- *Six Watersheds.* Choctawhatchee(a), Choctawhatchee(b), Choctawhatchee(c), Cloyo, Neuse, Ogeechee
- *One Flow Condition.* All flows
- *One Streamflow Variable.* Untransformed,
- *Two Periods.* Model calibration, Model evaluation
- *Three Atmospheric Input Sources.* Ground-based, TRMM, MERRA
- *Three Input Methods.* Nearest neighbor, Segmented, Weighted average

Tables 4.18 to 4.35 present a series of 18 tables that summarize five of the eight model performance statistics (R^2 , RMSE, MAE, NSE, MSE) for:

- *Six Watersheds.* Choctawhatchee(a), Choctawhatchee(b), Choctawhatchee(c), Cloyo, Neuse, Ogeechee

- *Three Flow Conditions.* All flows, Baseflows only, Stormflows only
- *Two Streamflow Variables.* Untransformed, Log-transformed
- *Two Periods.* Model calibration, Model evaluation
- *Three Atmospheric Input Sources.* Ground-based, TRMM, MERRA
- *Three Input Methods.* Nearest neighbor, Segmented, Weighted average

4.5 Data Reduction

In attempt to reduce the amount of redundancy in the statistical metrics used, correlation of the five metrics produced by BASSET was examined. A principal component analysis (PCA) was conducted on these metrics and combinations of each of the variables of the study (e.g. watershed model, simulation type, period, scale, input product, and input method). Table 4.4 shows the correlation matrix for the five metrics. Tables 4.5 - 4.11 show the results of the PCA for each combination.

Table 4.1: Means and standard deviations (Std Dev) for observed and simulated discharges.

Watershed	Period	Mean	Std Dev
Choctawhatchee(a)	30-yr Record	821	355
	Calibration	568	829
	Evaluation	807	1,006
Choctawhatchee(b)	28-yr Record	4,964	1,919
	Calibration	5,137	5,785
	Evaluation	6,717	4,789
Choctawhatchee(c)	30-yr Record	6,342	2,275
	Calibration	5,294	4,352
	Evaluation	5,796	7,116
Clyo	30-yr Record	10,238	4,240
	Calibration	7,844	4,894
	Evaluation	8,221	5,014
Neuse	30-yr Record	2,316	966
	Calibration	2,606	3,093
	Evaluation	1,829	1,867
Ogeechee	8-yr Record	813	347
	Calibration	846	997
	Evaluation	992	1,291

Table 4.2: Residual standard error ratios[†] for model calibration and evaluation periods.

Model Calibration Period							
Input Method [‡]		Choctawhatchee			Clyo	Ogeechee	Neuse
		(a)	(c)	(b)			
MERRA	NN	2.0	1.1	0.9	1.0	1.6	0.7
	SG	2.6	1.9	1.1	1.1	2.5	0.8
	WA	2.2	1.5	1.1	1.2	2.4	0.6
TRMM	NN	1.2	0.8	0.8	1.0	1.5	0.9
	SG	1.3	1.1	0.8	1.0	1.5	1.0
	WA	1.1	0.9	0.9	1.0	1.6	1.3

Model Evaluation Period							
Input Method [‡]		Choctawhatchee			Clyo	Ogeechee	Neuse
		(a)	(c)	(b)			
MERRA	NN	0.8	2.2	1.4	1.0	0.9	3.0
	SG	0.8	2.7	1.1	1.0	0.9	2.7
	WA	1.3	2.5	1.4	1.0	0.9	3.2
TRMM	NN	1.1	1.2	1.2	1.0	1.2	1.4
	SG	1.2	1.6	0.8	0.8	1.1	1.4
	WA	1.3	1.4	1.1	0.8	1.0	1.5

[†] Ratios less than one indicate that remotely sensed meteorologic data provides a superior fit to observed streamflow than ground-based data, and vice versa.

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.3: Double Mass Curve Results: Sites starting with a G, M or T indicate ground, MERRA or TRMM stations respectively. MRGED# refers simply to a weighted average grid with the # indicating a specific file, used for organizational purposes.

Site & Method	Product	R ²	Y- Intercept	Slope
Choctawhatchee (a)				
WA	GMRGED2	0.993	-29.776	0.0002
	MMRGED2	0.989	-34.500	0.0002
	TMRGED2	0.995	-33.184	0.0002
NN	AL013761	0.995	-28.947	0.0002
	M142243	0.989	-34.932	0.0002
	T3780326	0.995	-32.954	0.0002
Choctawhatchee (b)				
WA	GMRGED	0.998	-35.075	0.00003
	MMRGED5	0.996	-34.069	0.00002
	TMRGED	0.998	-33.582	0.00003
NN	AL013251	0.997	-42.129	0.00003
	M141243	0.996	-33.802	0.00002
	T3760325	0.998	-35.131	0.00003

Table 4.4: Correlation matrix of the five metrics calculated by BASSET.

	R^2	$RMSE$	MAE	NSE	$mNSE$
R^2	1				
RMSE	-0.25	1			
MAE	-0.24	0.99	1		
NSE	0.88	-0.20	-0.19	1	
mNSE	0.91	-0.04	-0.04	0.90	1

Table 4.5: Principal Components Analysis (PCA) results for the five BASSET metrics.

Metric	Principal Component				
	(1)	(2)	(3)	(4)	(5)
R^2	0.555	0.144	-0.597	-0.561	-0.017
RMSE	-0.245	0.659	-0.017	-0.033	-0.710
MAE	-0.240	0.661	0.027	-0.117	0.701
NSE	0.546	0.166	0.782	-0.247	-0.042
mNSE	0.526	0.284	-0.178	0.780	0.050
Variance	2.92	1.89	0.12	0.06	0.01
Proportion	58.3%	37.8%	2.4%	1.2%	0.2%
Cumulative	58.3%	96.1%	98.6%	99.8%	100.0%

Table 4.6: Principal Components Analysis (PCA) results for the five BASSET metrics and watershed models

Metric	Principal Component									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R^2	0.392	-0.369	-0.170	-0.051	-0.012	0.029	-0.224	0.635	0.474	0.012
RMSE	-0.105	0.302	-0.593	-0.151	-0.090	0.081	-0.067	0.012	0.020	0.710
MAE	-0.096	0.304	-0.594	-0.150	-0.089	0.036	-0.070	-0.052	0.138	-0.697
NSE	0.340	-0.414	-0.218	-0.047	0.087	0.019	0.180	-0.707	0.344	0.062
mNSE	0.399	-0.306	-0.288	-0.107	-0.011	0.081	-0.066	0.058	-0.796	-0.070
Model 1	0.229	0.295	0.233	-0.567	0.572	0.324	-0.219	-0.059	0.032	-0.003
Model 2	0.375	0.274	0.106	-0.407	-0.254	-0.447	0.571	0.126	0.018	0.012
Model 3	0.386	0.282	0.200	0.089	-0.481	-0.146	-0.635	-0.258	0.024	0.022
Model 4	0.358	0.304	0.040	0.416	-0.144	0.672	0.355	0.063	0.039	-0.019
Model 5	0.283	0.283	-0.168	0.519	0.576	-0.455	-0.026	0.029	-0.027	0.014
Variance	3.43	2.56	1.98	0.93	0.47	0.27	0.19	0.10	0.06	0.01
Proportion	34.3%	25.6%	19.8%	9.3%	4.7%	2.7%	1.9%	1.0%	0.6%	0.1%
Cumulative	34.3%	59.9%	79.7%	89.0%	93.7%	96.4%	98.3%	99.3%	99.9%	100.0%

Table 4.7: Principal Components Analysis (PCA) results for the five BASSET metrics and simulation type.

Metric	Principal Component						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R^2	0.493	0.155	0.246	0.005	-0.615	-0.543	-0.008
RMSE	-0.227	0.648	-0.105	-0.104	-0.012	-0.046	-0.711
MAE	-0.218	0.651	-0.133	-0.091	0.019	-0.104	0.702
NSE	0.489	0.178	0.206	0.066	0.774	-0.288	-0.029
mNSE	0.459	0.291	0.277	-0.056	-0.135	0.778	0.037
Simulation 1	-0.304	-0.085	0.682	-0.653	0.061	-0.068	0.017
Simulation 2	-0.339	0.101	0.571	0.740	-0.020	0.009	0.008
Variance	3.42	1.92	1.00	0.47	0.12	0.06	0.01
Proportion	48.9%	27.4%	14.3%	6.7%	1.7%	0.8%	0.1%
Cumulative	48.9%	76.2%	90.6%	97.3%	99.0%	99.9%	100.0%

Table 4.8: Principal Components Analysis (PCA) results for the five BASSET metrics and time period.

Metric	Principal Component					
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.552	0.146	0.078	0.588	0.567	0.020
RMSE	-0.245	0.658	-0.022	0.015	0.032	0.711
MAE	-0.240	0.661	-0.035	-0.025	0.119	-0.700
NSE	0.545	0.167	0.008	-0.785	0.239	0.039
mNSE	0.524	0.285	0.034	0.185	-0.779	-0.051
Period	-0.079	0.015	0.995	-0.047	-0.015	-0.009
Variance	2.93	1.89	0.99	0.12	0.06	0.01
Proportion	48.8%	31.5%	16.5%	2.0%	1.0%	0.2%
Cumulative	48.8%	80.3%	96.8%	98.8%	99.8%	100.0%

Table 4.9: Principal Components Analysis (PCA) results for the five BASSET metrics and watershed size.

Metric	Principal Component					
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.507	0.266	-0.016	0.633	0.520	0.027
RMSE	-0.351	0.483	-0.392	0.063	-0.029	0.697
MAE	-0.348	0.491	-0.351	0.003	0.112	-0.709
NSE	0.498	0.273	-0.148	-0.755	0.287	0.059
mNSE	0.452	0.383	0.002	0.130	-0.791	-0.081
Scale	-0.214	0.484	0.838	-0.091	0.095	0.040
Variance	2.98	2.41	0.43	0.12	0.06	0.01
Proportion	49.6%	40.2%	7.1%	2.0%	1.0%	0.1%
Cumulative	49.6%	89.8%	96.9%	98.9%	99.9%	100.0%

Table 4.10: Principal Components Analysis (PCA) results for the five BASSET metrics and input product.

Metric	Principal Component						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R ²	-0.540	-0.098	0.107	-0.010	-0.631	-0.536	-0.030
RMSE	0.208	-0.669	0.057	-0.016	0.002	-0.039	-0.710
MAE	0.205	-0.669	0.065	0.042	-0.001	-0.111	0.701
NSE	-0.527	-0.117	0.088	0.361	0.706	-0.267	-0.028
mNSE	-0.519	-0.240	0.085	0.082	-0.179	0.791	0.035
Input 1	-0.057	0.040	0.763	-0.615	0.183	-0.003	0.021
Input 2	0.269	0.148	0.619	0.695	-0.193	0.041	-0.029
Variance	3.10	1.91	1.46	0.35	0.10	0.06	0.01
Proportion	44.3%	27.3%	20.9%	5.0%	1.5%	0.9%	0.1%
Cumulative	44.3%	71.7%	92.5%	97.5%	99.0%	99.9%	100.0%

Table 4.11: Principal Components Analysis (PCA) results for the five BASSET metrics and input method.

Metric	Principal Component						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R^2	0.554	0.140	-0.035	-0.032	-0.594	-0.564	-0.018
RMSE	-0.242	0.659	-0.022	-0.002	-0.016	-0.033	-0.710
MAE	-0.237	0.662	-0.026	-0.005	0.027	-0.117	0.701
NSE	0.544	0.160	-0.077	-0.016	0.782	-0.243	-0.041
mNSE	0.525	0.278	-0.062	-0.009	-0.182	0.779	0.050
Method 1	0.038	0.037	0.708	-0.704	0.026	0.015	0.000
Method 2	0.079	0.056	0.698	0.710	0.014	-0.007	0.003
Variance	2.93	1.89	1.49	0.50	0.12	0.06	0.01
Proportion	41.8%	27.0%	21.3%	7.1%	1.7%	0.9%	0.1%
Cumulative	44.3%	71.7%	92.5%	97.5%	99.0%	99.9%	100.0%

Table 4.12: Model calibration and evaluation results[†] for Choctawhatchee(a).

Model Calibration Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	885	606	0.067	-6.7	0.60
	SG	917	655	0.152	-15.2	0.58
	WA	761	599	0.054	-5.4	0.56
MERRA	NN	452	484	-0.148	14.8	0.95
	SG	468	486	-0.144	14.4	0.93
	WA	458	483	-0.149	14.9	0.95
TRMM	NN	906	591	0.04	-4.0	0.93
	SG	780	563	-0.008	0.8	1.48
	WA	820	565	-0.005	0.5	0.88

Model Evaluation Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	914	817	0.012	-1.2	0.80
	SG	875	779	-0.035	3.5	0.65
	WA	589	679	-0.159	15.9	0.72
MERRA	NN	436	579	-0.282	28.2	0.99
	SG	408	554	-0.314	31.4	0.99
	WA	427	566	-0.298	29.8	0.99
TRMM	NN	816	699	-0.133	13.3	0.75
	SG	665	684	-0.152	15.2	0.76
	WA	679	677	-0.161	16.1	0.77

[†] Mean, standard deviation (Std Dev), relative bias (R_b), percent bias (PBIAS), and the ratio of the root mean squared error to the standard deviation of observed data (RSR).

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.13: Model calibration and evaluation results[†] for Choctawhatchee(b).

Model Calibration Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	3,292	4,401	-0.143	14.3	0.88
	SG	4,857	4,902	-0.046	4.6	0.59
	WA	5,046	4,998	-0.027	2.7	0.62
MERRA	NN	1,821	3,325	-0.353	35.3	1.00
	SG	2,730	3,463	-0.326	32.6	1.02
	WA	2,692	3,402	-0.338	33.8	1.02
TRMM	NN	4,969	5,085	-0.01	1.0	0.63
	SG	4,721	5,092	-0.009	0.9	0.58
	WA	4,863	5,124	-0.003	0.3	0.58

Model Evaluation Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	3,323	3,889	-0.188	18.8	0.77
	SG	7,537	5,156	0.077	-7.7	0.77
	WA	7,174	4,722	-0.014	1.4	0.74
MERRA	NN	2,208	3,318	-0.307	30.7	0.90
	SG	3,043	3,445	-0.281	28.1	0.88
	WA	2,998	3,395	-0.291	29.1	0.89
TRMM	NN	8,074	5,345	0.116	-11.6	0.82
	SG	7,857	5,231	0.092	-9.2	0.75
	WA	7,813	5,222	0.09	-9.0	0.76

[†] Mean, standard deviation (Std Dev), relative bias (R_b), percent bias (PBIAS), and the ratio of the root mean squared error to the standard deviation of observed data (RSR).

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.14: Model calibration and evaluation results[†] for Choctawhatchee(c).

Model Calibration Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	3,679	5,124	-0.032	3.2	0.78
	SG	4,114	5,149	-0.027	2.7	0.75
	WA	4,294	5,226	-0.013	1.3	0.72
MERRA	NN	1,985	3,750	-0.292	29.2	0.97
	SG	1,982	3,798	-0.283	28.3	0.96
	WA	1,914	3,694	-0.302	30.2	0.97
TRMM	NN	3,761	4,879	-0.078	7.8	0.78
	SG	3,746	5,006	-0.054	5.4	0.70
	WA	3,602	4,966	-0.062	6.2	0.71

Model Evaluation Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	3,968	5,514	-0.049	4.9	0.76
	SG	6,391	5,850	0.009	-0.9	0.71
	WA	7,479	5,961	0.028	-2.8	0.75
MERRA	NN	2,200	3,979	-0.313	31.3	0.93
	SG	2,302	4,020	-0.306	30.6	0.94
	WA	2,243	3,913	-0.325	32.5	0.94
TRMM	NN	6,055	5,815	0.003	-0.3	0.72
	SG	5,797	5,375	-0.073	7.3	0.67
	WA	5,628	5,522	-0.047	4.7	0.68

[†] Mean, standard deviation (Std Dev), relative bias (R_b), percent bias (PBIAS), and the ratio of the root mean squared error to the standard deviation of observed data (RSR).

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.15: Model calibration and evaluation results[†] for Clyo.

Model Calibration Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	5,633	8,049	0.026	-2.6	0.69
	SG	5,394	7,996	0.019	-1.9	0.67
	WA	5,305	7,916	0.009	-0.9	0.66
MERRA	NN	4,242	7,564	-0.036	3.6	0.71
	SG	4,226	7,557	-0.037	3.7	0.72
	WA	4,266	7,596	-0.032	3.2	0.73
TRMM	NN	5,393	7,976	0.017	-1.7	0.69
	SG	5,417	7,978	0.017	-1.7	0.67
	WA	5,301	7,943	0.013	-1.3	0.67

Model Evaluation Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	5,461	8,209	-0.001	0.1	0.67
	SG	5,570	8,462	0.029	-2.9	0.68
	WA	5,694	8,461	0.029	-2.9	0.68
MERRA	NN	4,633	7,350	-0.106	10.6	0.69
	SG	4,640	7,355	-0.105	10.5	0.69
	WA	4,650	7,370	-0.104	10.4	0.69
TRMM	NN	5,664	8,776	0.068	-6.8	0.73
	SG	5,740	8,796	0.07	-7.0	0.72
	WA	5,506	8,689	0.057	-5.7	0.68

[†] Mean, standard deviation (Std Dev), relative bias (R_b), percent bias (PBIAS), and the ratio of the root mean squared error to the standard deviation of observed data (RSR).

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.16: Model calibration and evaluation results[†] for Neuse.

Model Calibration Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	3,206	2,496	-0.042	4.2	0.78
	SG	3,417	2,640	0.013	-1.3	0.74
	WA	3,509	2,647	0.016	-1.6	0.75
MERRA	NN	1,967	2,178	-0.164	16.4	0.82
	SG	2,382	2,242	-0.14	14.0	0.79
	WA	932	1,335	-0.488	48.8	0.99
TRMM	NN	3,823	2,512	-0.036	3.6	0.92
	SG	3,763	2,593	-0.005	0.5	0.85
	WA	3,870	2,567	-0.015	1.5	0.89

Model Evaluation Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	1,905	1,575	-0.139	13.9	0.99
	SG	2,511	2,317	0.267	-26.7	0.96
	WA	2,553	2,259	0.235	-23.5	0.97
MERRA	NN	1,526	1,698	-0.072	7.2	0.84
	SG	1,622	1,679	-0.082	8.2	0.90
	WA	1,113	2,162	0.182	-18.2	0.89
TRMM	NN	2,266	1,998	0.092	-9.2	1.05
	SG	2,335	2,163	0.182	-18.2	1.02
	WA	2,419	2,164	0.183	-18.3	1.04

[†] Mean, standard deviation (Std Dev), relative bias (R_b), percent bias (PBIAS), and the ratio of the root mean squared error to the standard deviation of observed data (RSR).

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.17: Model calibration and evaluation results[†] for Ogeechee.

Model Calibration Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	1,089	888	0.049	-4.9	0.60
	SG	1,373	1,024	0.21	-21.0	0.84
	WA	1,081	902	0.065	-6.5	0.53
MERRA	NN	759	852	0.007	-0.7	0.85
	SG	765	840	-0.008	0.8	0.85
	WA	785	855	0.01	-1.0	0.85
TRMM	NN	880	867	0.025	-2.5	0.67
	SG	1,002	902	0.066	-6.6	0.65
	WA	1,243	960	0.134	-13.4	0.73

Model Evaluation Period						
Method [‡]		Std Dev	Mean	R _b	PBIAS	RSR
Ground	NN	1,276	1,105	0.115	-11.5	0.57
	SG	1,890	1,433	0.445	-44.5	0.88
	WA	1,573	1,349	0.361	-36.1	0.63
MERRA	NN	952	1,137	0.146	-14.6	0.72
	SG	975	1,152	0.162	-16.2	0.82
	WA	1,001	1,173	0.183	-18.3	0.83
TRMM	NN	1,662	1,302	0.312	-31.2	0.84
	SG	1,614	1,347	0.359	-35.9	0.83
	WA	2,250	1,582	0.595	-59.5	1.22

[†] Mean, standard deviation (Std Dev), relative bias (R_b), percent bias (PBIAS), and the ratio of the root mean squared error to the standard deviation of observed data (RSR).

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.18: Model calibration and evaluation results[†] for Choctawhatchee(a) - All Flows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.70	495	256	0.64	0.40	0.64	0.29	0.23	0.50	0.29
	SG	0.73	484	226	0.66	0.47	0.77	0.23	0.17	0.70	0.46
	WA	0.70	461	230	0.69	0.46	0.68	0.28	0.20	0.55	0.36
MERRA	NN	0.13	792	370	0.09	0.13	0.23	0.40	0.31	0.07	0.04
	SG	0.16	774	361	0.13	0.15	0.25	0.39	0.30	0.13	0.06
	WA	0.15	784	365	0.11	0.14	0.24	0.40	0.30	0.09	0.05
TRMM	NN	0.38	767	302	0.14	0.29	0.51	0.32	0.25	0.39	0.23
	SG	0.39	701	278	0.29	0.35	0.59	0.28	0.22	0.54	0.31
	WA	0.37	728	282	0.23	0.34	0.60	0.28	0.22	0.54	0.31

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.43	803	362	0.36	0.33	0.63	0.25	0.20	0.59	0.34
	SG	0.59	652	289	0.58	0.46	0.74	0.21	0.17	0.71	0.44
	WA	0.52	721	311	0.49	0.42	0.62	0.26	0.20	0.53	0.32
MERRA	NN	0.08	1,000	511	0.01	0.05	0.13	0.42	0.33	-0.23	-0.12
	SG	0.09	995	498	0.02	0.08	0.15	0.41	0.32	-0.14	-0.07
	WA	0.09	998	507	0.02	0.06	0.14	0.42	0.33	-0.21	-0.11
TRMM	NN	0.46	759	387	0.43	0.28	0.48	0.33	0.26	0.25	0.13
	SG	0.44	764	381	0.42	0.29	0.50	0.32	0.26	0.29	0.14
	WA	0.43	770	384	0.41	0.29	0.50	0.32	0.26	0.28	0.14

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.19: Model calibration and evaluation results[†] for Choctawhatchee(a) - Stormflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.65	436	200	0.62	0.39	0.43	0.49	0.35	0.22	0.17
	SG	0.67	436	189	0.62	0.43	0.55	0.42	0.29	0.42	0.30
	WA	0.65	423	192	0.64	0.42	0.50	0.43	0.31	0.40	0.26
MERRA	NN	0.10	680	279	0.07	0.15	0.18	0.53	0.40	0.06	0.04
	SG	0.12	672	274	0.09	0.16	0.20	0.52	0.39	0.10	0.06
	WA	0.11	676	276	0.08	0.16	0.19	0.53	0.40	0.08	0.05
TRMM	NN	0.27	716	255	-0.02	0.23	0.31	0.52	0.39	0.09	0.07
	SG	0.28	663	239	0.14	0.29	0.36	0.51	0.38	0.14	0.10
	WA	0.26	677	238	0.08	0.27	0.41	0.46	0.35	0.32	0.17

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.34	736	291	0.27	0.31	0.38	0.44	0.32	0.32	0.23
	SG	0.51	611	245	0.50	0.42	0.48	0.41	0.30	0.41	0.28
	WA	0.45	657	259	0.42	0.39	0.32	0.48	0.34	0.19	0.17
MERRA	NN	0.09	838	375	0.06	0.11	0.09	0.57	0.44	-0.13	-0.07
	SG	0.10	834	364	0.06	0.14	0.09	0.55	0.42	-0.06	-0.03
	WA	0.09	836	371	0.06	0.12	0.09	0.56	0.43	-0.11	-0.06
TRMM	NN	0.40	689	320	0.37	0.25	0.22	0.58	0.42	-0.18	-0.04
	SG	0.39	677	305	0.38	0.28	0.27	0.52	0.40	0.04	0.03
	WA	0.38	683	309	0.37	0.27	0.25	0.53	0.40	-0.01	0.01

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.20: Model calibration and evaluation results[†] for Choctawhatchee(a) - Baseflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.85	119	81	0.70	0.42	0.72	0.23	0.19	0.60	0.35
	SG	0.90	105	62	0.76	0.55	0.86	0.16	0.12	0.81	0.58
	WA	0.85	93	63	0.81	0.55	0.76	0.21	0.15	0.66	0.47
MERRA	NN	0.22	200	129	0.13	0.07	0.22	0.36	0.28	0.00	0.01
	SG	0.28	190	124	0.22	0.11	0.25	0.35	0.28	0.07	0.04
	WA	0.24	196	127	0.17	0.09	0.23	0.36	0.28	0.02	0.02
TRMM	NN	0.70	141	83	0.57	0.40	0.60	0.25	0.19	0.53	0.35
	SG	0.73	116	72	0.69	0.47	0.69	0.21	0.16	0.67	0.44
	WA	0.70	130	76	0.64	0.45	0.70	0.21	0.16	0.66	0.43

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.67	161	105	0.59	0.37	0.74	0.18	0.15	0.71	0.43
	SG	0.81	117	75	0.78	0.54	0.84	0.14	0.12	0.81	0.55
	WA	0.72	143	86	0.68	0.48	0.76	0.19	0.14	0.68	0.44
MERRA	NN	0.09	267	185	-0.13	-0.12	0.12	0.39	0.32	-0.36	-0.24
	SG	0.10	265	181	-0.12	-0.10	0.15	0.38	0.31	-0.27	-0.20
	WA	0.10	267	184	-0.13	-0.11	0.13	0.39	0.32	-0.35	-0.23
TRMM	NN	0.64	159	113	0.60	0.31	0.58	0.26	0.20	0.41	0.22
	SG	0.57	171	118	0.54	0.29	0.60	0.25	0.20	0.43	0.21
	WA	0.57	172	119	0.53	0.28	0.60	0.25	0.21	0.41	0.20

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.21: Model calibration and evaluation results[†] for Choctawhatchee(b) - All Flows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.43	3,374	2,016	0.40	0.32	0.61	0.22	0.17	0.44	0.24
	SG	0.50	3,262	1,775	0.44	0.40	0.68	0.18	0.14	0.62	0.39
	WA	0.54	3,131	1,783	0.48	0.40	0.68	0.18	0.14	0.62	0.39
MERRA	SG	0.18	4,231	2,603	0.05	0.12	0.25	0.28	0.23	0.02	0.00
	SG	0.19	4,195	2,611	0.07	0.12	0.22	0.29	0.23	0.02	-0.01
	WA	0.19	4,226	2,619	0.06	0.12	0.22	0.29	0.23	-0.01	-0.02
TRMM	SG	0.45	3,376	1,951	0.40	0.34	0.58	0.20	0.15	0.53	0.31
	SG	0.53	3,067	1,818	0.50	0.39	0.62	0.18	0.15	0.59	0.35
	WA	0.52	3,068	1,804	0.50	0.39	0.62	0.19	0.15	0.59	0.35

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.43	5,412	2,566	0.42	0.32	0.52	0.24	0.19	0.47	0.31
	SG	0.52	5,064	2,182	0.49	0.42	0.70	0.19	0.14	0.67	0.49
	WA	0.54	5,344	2,184	0.44	0.42	0.70	0.20	0.14	0.64	0.46
MERRA	SG	0.24	6,593	3,090	0.14	0.18	0.26	0.29	0.23	0.20	0.13
	SG	0.19	6,681	3,223	0.12	0.14	0.22	0.31	0.25	0.12	0.07
	WA	0.20	6,706	3,217	0.11	0.14	0.22	0.31	0.25	0.11	0.07
TRMM	SG	0.51	5,095	2,573	0.49	0.32	0.58	0.24	0.18	0.48	0.32
	SG	0.56	4,748	2,344	0.55	0.38	0.65	0.22	0.17	0.56	0.36
	WA	0.54	4,849	2,375	0.54	0.37	0.65	0.21	0.17	0.59	0.38

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.22: Model calibration and evaluation results[†] for Choctawhatchee(b) - Stormflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.31	2,890	1,639	0.25	0.24	0.43	0.31	0.24	0.20	0.12
	SG	0.35	2,941	1,496	0.22	0.31	0.53	0.26	0.20	0.44	0.27
	WA	0.39	2,854	1,524	0.27	0.30	0.51	0.26	0.20	0.43	0.27
MERRA	SG	0.14	3,238	1,861	0.06	0.14	0.16	0.34	0.27	0.03	0.01
	SG	0.15	3,210	1,874	0.07	0.13	0.14	0.34	0.27	0.02	0.00
	WA	0.15	3,221	1,871	0.07	0.14	0.15	0.34	0.27	0.01	-0.01
TRMM	SG	0.31	2,985	1,625	0.20	0.25	0.42	0.28	0.22	0.31	0.18
	SG	0.39	2,736	1,523	0.33	0.30	0.47	0.27	0.21	0.40	0.23
	WA	0.37	2,740	1,515	0.33	0.30	0.46	0.27	0.21	0.38	0.22

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.32	4,750	2,122	0.32	0.23	0.37	0.33	0.25	0.27	0.18
	SG	0.40	4,671	1,938	0.34	0.30	0.56	0.27	0.20	0.51	0.34
	WA	0.42	4,971	1,960	0.25	0.29	0.54	0.28	0.21	0.46	0.31
MERRA	SG	0.21	5,361	2,183	0.13	0.21	0.21	0.35	0.27	0.19	0.13
	SG	0.18	5,399	2,235	0.12	0.19	0.19	0.35	0.28	0.14	0.11
	WA	0.18	5,415	2,228	0.11	0.19	0.19	0.35	0.28	0.14	0.10
TRMM	SG	0.39	4,636	2,187	0.35	0.21	0.43	0.33	0.25	0.26	0.17
	SG	0.45	4,321	1,986	0.43	0.28	0.45	0.33	0.24	0.26	0.21
	WA	0.43	4,376	2,004	0.42	0.27	0.48	0.30	0.24	0.37	0.24

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.23: Model calibration and evaluation results[†] for Choctawhatchee(b) - Baseflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.64	839	577	0.63	0.44	0.75	0.16	0.13	0.64	0.40
	SG	0.78	659	444	0.77	0.57	0.81	0.12	0.10	0.79	0.54
	WA	0.82	596	421	0.81	0.59	0.83	0.12	0.09	0.80	0.56
MERRA	SG	0.25	1,343	947	0.05	0.07	0.31	0.26	0.22	0.01	-0.03
	SG	0.25	1,334	952	0.06	0.07	0.27	0.26	0.22	0.00	-0.03
	WA	0.25	1,351	958	0.04	0.06	0.27	0.27	0.22	-0.03	-0.05
TRMM	SG	0.72	749	522	0.70	0.49	0.74	0.14	0.11	0.72	0.47
	SG	0.78	653	475	0.77	0.54	0.77	0.13	0.10	0.76	0.51
	WA	0.79	649	469	0.78	0.54	0.77	0.13	0.10	0.77	0.51

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.68	1,140	666	0.66	0.47	0.66	0.18	0.14	0.65	0.44
	SG	0.83	822	434	0.82	0.65	0.86	0.11	0.08	0.85	0.66
	WA	0.85	852	483	0.81	0.61	0.87	0.12	0.09	0.84	0.63
MERRA	SG	0.27	1,821	1,098	0.13	0.12	0.28	0.27	0.23	0.17	0.09
	SG	0.20	1,875	1,164	0.08	0.07	0.22	0.29	0.24	0.06	0.02
	WA	0.20	1,885	1,161	0.07	0.07	0.22	0.29	0.25	0.05	0.01
TRMM	SG	0.77	944	638	0.77	0.49	0.72	0.17	0.13	0.68	0.46
	SG	0.81	853	523	0.81	0.58	0.80	0.14	0.11	0.77	0.55
	WA	0.79	901	548	0.79	0.56	0.79	0.14	0.11	0.77	0.55

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.24: Model calibration and evaluation results[†] for Choctawhatchee(c) - All Flows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.25	5,065	2,474	0.23	0.26	0.45	0.26	0.20	0.43	0.24
	SG	0.66	3,396	1,852	0.66	0.45	0.68	0.20	0.15	0.66	0.43
	WA	0.63	3,572	1,881	0.62	0.44	0.69	0.20	0.15	0.66	0.42
MERRA	NN	0.10	5,767	2,872	0.01	0.14	0.12	0.35	0.27	-0.10	-0.01
	SG	0.08	5,887	2,956	-0.04	0.12	0.12	0.35	0.27	-0.07	-0.03
	WA	0.08	5,911	2,951	-0.04	0.12	0.12	0.35	0.27	-0.07	-0.02
TRMM	NN	0.61	3,646	1,984	0.60	0.41	0.64	0.21	0.16	0.62	0.39
	SG	0.66	3,381	1,828	0.66	0.45	0.70	0.19	0.15	0.69	0.43
	WA	0.66	3,369	1,831	0.66	0.45	0.69	0.19	0.15	0.67	0.42

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.47	5,144	2,446	0.41	0.35	0.52	0.28	0.22	0.52	0.33
	SG	0.55	5,182	2,318	0.40	0.38	0.69	0.24	0.18	0.65	0.46
	WA	0.55	4,978	2,166	0.45	0.42	0.68	0.24	0.18	0.65	0.46
MERRA	NN	0.26	6,072	2,958	0.18	0.21	0.27	0.35	0.28	0.24	0.15
	SG	0.27	5,917	2,973	0.22	0.21	0.27	0.35	0.28	0.24	0.15
	WA	0.26	5,950	2,950	0.21	0.21	0.28	0.35	0.28	0.25	0.16
TRMM	NN	0.55	5,523	2,529	0.32	0.33	0.60	0.26	0.21	0.56	0.38
	SG	0.60	5,044	2,330	0.44	0.38	0.66	0.24	0.19	0.63	0.42
	WA	0.58	5,119	2,348	0.42	0.37	0.65	0.25	0.20	0.62	0.41

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.25: Model calibration and evaluation results[†] for Choctawhatchee(c) - Stormflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.19	3,620	1,755	0.16	0.21	0.33	0.31	0.24	0.28	0.15
	SG	0.55	2,673	1,394	0.54	0.38	0.57	0.24	0.18	0.54	0.33
	WA	0.52	2,800	1,396	0.50	0.37	0.57	0.25	0.19	0.53	0.33
MERRA	NN	0.08	3,935	1,854	0.00	0.17	0.09	0.38	0.28	-0.09	0.00
	SG	0.07	4,023	1,896	-0.04	0.15	0.10	0.37	0.28	-0.06	-0.01
	WA	0.07	4,038	1,889	-0.05	0.15	0.10	0.37	0.28	-0.06	0.00
TRMM	NN	0.48	2,928	1,504	0.45	0.33	0.51	0.26	0.20	0.48	0.29
	SG	0.54	2,694	1,392	0.53	0.38	0.59	0.24	0.18	0.56	0.34
	WA	0.54	2,708	1,395	0.53	0.38	0.57	0.24	0.18	0.55	0.33

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.37	3,735	1,736	0.34	0.29	0.42	0.32	0.26	0.41	0.24
	SG	0.43	4,129	1,695	0.19	0.31	0.60	0.28	0.21	0.54	0.38
	WA	0.45	3,882	1,573	0.29	0.36	0.60	0.28	0.21	0.56	0.37
MERRA	NN	0.22	4,223	1,890	0.15	0.23	0.25	0.37	0.29	0.22	0.14
	SG	0.22	4,131	1,880	0.19	0.23	0.25	0.37	0.29	0.22	0.14
	WA	0.22	4,154	1,871	0.18	0.24	0.25	0.36	0.29	0.23	0.15
TRMM	NN	0.42	4,359	1,812	0.10	0.26	0.53	0.30	0.23	0.48	0.32
	SG	0.47	4,026	1,671	0.23	0.32	0.59	0.28	0.22	0.54	0.35
	WA	0.46	4,091	1,686	0.21	0.31	0.58	0.28	0.22	0.53	0.34

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.26: Model calibration and evaluation results[†] for Choctawhatchee(c) - Baseflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.34	1,711	872	0.32	0.31	0.54	0.22	0.18	0.53	0.31
	SG	0.79	966	580	0.78	0.54	0.76	0.16	0.13	0.75	0.51
	WA	0.75	1,028	606	0.75	0.52	0.77	0.16	0.13	0.76	0.50
MERRA	NN	0.13	2,063	1,097	0.01	0.13	0.13	0.34	0.26	-0.11	-0.02
	SG	0.10	2,102	1,136	-0.03	0.10	0.13	0.34	0.27	-0.09	-0.04
	WA	0.09	2,111	1,137	-0.04	0.10	0.13	0.34	0.27	-0.08	-0.04
TRMM	NN	0.77	989	600	0.77	0.52	0.73	0.17	0.13	0.73	0.47
	SG	0.80	935	552	0.80	0.56	0.78	0.15	0.12	0.77	0.51
	WA	0.81	911	553	0.81	0.56	0.77	0.16	0.13	0.76	0.50

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.59	1,688	838	0.50	0.40	0.61	0.25	0.20	0.60	0.39
	SG	0.71	1,431	774	0.64	0.45	0.76	0.20	0.16	0.74	0.53
	WA	0.69	1,445	743	0.63	0.47	0.75	0.20	0.16	0.73	0.52
MERRA	NN	0.31	2,120	1,128	0.21	0.20	0.29	0.34	0.28	0.26	0.16
	SG	0.31	2,057	1,153	0.26	0.18	0.28	0.34	0.28	0.25	0.15
	WA	0.31	2,068	1,144	0.25	0.19	0.29	0.34	0.28	0.26	0.16
TRMM	NN	0.70	1,560	878	0.57	0.38	0.67	0.23	0.19	0.64	0.42
	SG	0.76	1,386	793	0.66	0.44	0.72	0.21	0.18	0.70	0.47
	WA	0.75	1,401	798	0.65	0.43	0.71	0.22	0.18	0.69	0.46

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.27: Model calibration and evaluation results[†] for Clyo - All Flows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.64	3,383	1,598	0.52	0.47	0.74	0.10	0.07	0.70	0.49
	SG	0.64	3,267	1,571	0.55	0.48	0.74	0.10	0.07	0.71	0.50
	WA	0.64	3,254	1,558	0.56	0.49	0.75	0.10	0.07	0.72	0.50
MERRA	SG	0.52	3,493	1,871	0.49	0.38	0.57	0.12	0.09	0.55	0.33
	SG	0.51	3,519	1,872	0.48	0.38	0.57	0.12	0.09	0.55	0.33
	WA	0.50	3,563	1,916	0.47	0.37	0.55	0.12	0.09	0.53	0.32
TRMM	SG	0.62	3,396	1,675	0.52	0.45	0.73	0.10	0.07	0.68	0.46
	SG	0.64	3,281	1,621	0.55	0.47	0.74	0.10	0.07	0.70	0.47
	WA	0.64	3,255	1,613	0.56	0.47	0.74	0.10	0.07	0.71	0.47

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.64	3,337	1,804	0.56	0.45	0.70	0.11	0.08	0.65	0.46
	SG	0.64	3,406	1,840	0.54	0.44	0.70	0.11	0.08	0.65	0.46
	WA	0.65	3,403	1,832	0.54	0.44	0.71	0.11	0.08	0.65	0.46
MERRA	SG	0.58	3,468	2,035	0.52	0.38	0.61	0.13	0.10	0.51	0.33
	SG	0.58	3,462	2,043	0.52	0.38	0.60	0.13	0.10	0.50	0.32
	WA	0.58	3,459	2,051	0.52	0.38	0.59	0.14	0.10	0.49	0.32
TRMM	SG	0.60	3,671	2,047	0.46	0.38	0.64	0.13	0.09	0.57	0.40
	SG	0.62	3,620	2,051	0.48	0.38	0.65	0.12	0.09	0.58	0.40
	WA	0.63	3,431	1,937	0.53	0.41	0.68	0.12	0.08	0.62	0.43

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.28: Model calibration and evaluation results[†] for Clio - Stormflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
NSE	mNSE										
Ground	SG	0.40	3,172	1,458	0.09	0.27	0.47	0.16	0.10	0.31	0.28
	SG	0.41	3,087	1,446	0.14	0.27	0.48	0.16	0.10	0.32	0.28
	WA	0.41	3,068	1,423	0.15	0.29	0.47	0.16	0.10	0.33	0.29
MERRA	SG	0.28	3,142	1,550	0.11	0.22	0.30	0.18	0.12	0.12	0.16
	SG	0.27	3,164	1,555	0.10	0.22	0.29	0.18	0.12	0.11	0.16
	WA	0.26	3,210	1,592	0.07	0.20	0.28	0.18	0.12	0.08	0.14
TRMM	SG	0.39	3,190	1,522	0.08	0.24	0.46	0.16	0.11	0.29	0.24
	SG	0.42	3,086	1,478	0.14	0.26	0.47	0.16	0.10	0.32	0.26
	WA	0.40	3,074	1,473	0.15	0.26	0.49	0.16	0.10	0.35	0.26

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.46	3,103	1,647	0.23	0.28	0.47	0.18	0.12	0.28	0.26
	SG	0.46	3,148	1,678	0.21	0.26	0.46	0.18	0.12	0.28	0.26
	WA	0.48	3,144	1,666	0.21	0.27	0.47	0.18	0.12	0.28	0.26
MERRA	SG	0.39	3,052	1,681	0.26	0.26	0.35	0.20	0.14	0.09	0.17
	SG	0.40	3,035	1,681	0.26	0.26	0.35	0.20	0.14	0.08	0.17
	WA	0.40	3,032	1,685	0.27	0.26	0.34	0.20	0.14	0.08	0.17
TRMM	SG	0.42	3,400	1,808	0.09	0.21	0.38	0.20	0.13	0.09	0.21
	SG	0.45	3,295	1,778	0.13	0.22	0.43	0.19	0.13	0.22	0.23
	WA	0.45	3,188	1,718	0.20	0.25	0.41	0.19	0.13	0.20	0.24

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.29: Model calibration and evaluation results[†] for Clio - Stormflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.94	520	287	0.91	0.75	0.94	0.05	0.03	0.93	0.72
	SG	0.94	463	268	0.93	0.76	0.94	0.04	0.03	0.94	0.73
	WA	0.93	473	276	0.93	0.76	0.94	0.04	0.03	0.94	0.73
MERRA	SG	0.86	715	477	0.84	0.58	0.78	0.08	0.06	0.78	0.49
	SG	0.86	722	476	0.84	0.58	0.78	0.08	0.06	0.78	0.50
	WA	0.85	725	484	0.83	0.57	0.77	0.08	0.06	0.77	0.49
TRMM	SG	0.92	510	297	0.92	0.74	0.93	0.05	0.04	0.93	0.70
	SG	0.93	487	290	0.93	0.74	0.93	0.05	0.04	0.93	0.71
	WA	0.94	462	274	0.93	0.76	0.94	0.04	0.03	0.94	0.72

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.91	503	316	0.91	0.73	0.92	0.05	0.04	0.92	0.72
	SG	0.91	541	309	0.90	0.74	0.92	0.05	0.04	0.92	0.73
	WA	0.91	540	313	0.90	0.73	0.92	0.05	0.04	0.92	0.73
MERRA	SG	0.85	743	507	0.80	0.57	0.83	0.09	0.07	0.76	0.51
	SG	0.84	754	517	0.80	0.56	0.81	0.09	0.07	0.74	0.49
	WA	0.84	755	521	0.80	0.56	0.80	0.09	0.07	0.73	0.48
TRMM	SG	0.88	639	419	0.86	0.65	0.87	0.07	0.05	0.85	0.62
	SG	0.87	649	428	0.85	0.64	0.87	0.07	0.05	0.85	0.62
	WA	0.89	583	388	0.88	0.67	0.90	0.06	0.05	0.88	0.65

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.30: Model calibration and evaluation results[†] for Neuse - All Flows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.50	2,401	1,272	0.40	0.36	0.61	0.28	0.21	0.52	0.35
	SG	0.57	2,287	1,110	0.45	0.44	0.71	0.23	0.17	0.67	0.48
	WA	0.57	2,332	1,122	0.43	0.44	0.72	0.23	0.17	0.68	0.49
MERRA	SG	0.35	2,534	1,427	0.33	0.28	0.42	0.32	0.25	0.38	0.25
	SG	0.41	2,431	1,393	0.38	0.30	0.48	0.30	0.23	0.44	0.29
	WA	0.20	3,073	1,552	0.01	0.22	0.37	0.38	0.30	0.09	0.08
TRMM	SG	0.47	2,838	1,385	0.16	0.30	0.52	0.30	0.23	0.45	0.30
	SG	0.52	2,619	1,241	0.28	0.38	0.61	0.26	0.20	0.57	0.38
	WA	0.50	2,756	1,248	0.21	0.37	0.62	0.26	0.20	0.58	0.39

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SG	0.28	1,844	962	0.02	0.31	0.56	0.30	0.23	0.50	0.35
	SG	0.53	1,797	910	0.07	0.35	0.71	0.26	0.19	0.62	0.45
	WA	0.52	1,814	882	0.05	0.37	0.72	0.25	0.18	0.64	0.48
MERRA	SG	0.34	1,576	931	0.29	0.33	0.57	0.29	0.23	0.51	0.35
	SG	0.30	1,678	1,003	0.19	0.28	0.50	0.30	0.24	0.49	0.31
	WA	0.26	1,653	1,218	0.22	0.13	0.45	0.39	0.33	0.14	0.07
TRMM	SG	0.32	1,964	1,107	-0.11	0.2	-	-	-	-	-
	SG	0.39	1,903	1,071	-0.04	0.23	0.56	0.32	0.25	0.42	0.30
	WA	0.39	1,948	1,071	-0.09	0.23	0.57	0.32	0.25	0.41	0.30

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.31: Model calibration and evaluation results[†] for Neuse - Stormflows.

Model Calibration Period											
Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.34	2,048	1,019	0.05	0.24	0.44	0.39	0.30	0.27	0.22
	SG	0.42	1,985	917	0.11	0.32	0.55	0.34	0.25	0.45	0.34
	WA	0.42	2,031	926	0.07	0.31	0.56	0.33	0.25	0.48	0.36
MERRA	NN	0.27	1,838	1,006	0.23	0.25	0.33	0.39	0.30	0.28	0.21
	SG	0.32	1,841	999	0.23	0.25	0.38	0.37	0.29	0.34	0.24
	WA	0.13	2,100	1,031	0.00	0.23	0.26	0.45	0.34	0.06	0.10
TRMM	NN	0.31	2,452	1,100	-0.36	0.18	0.37	0.40	0.31	0.24	0.19
	SG	0.36	2,278	1,013	-0.18	0.24	0.44	0.37	0.29	0.35	0.25
	WA	0.34	2,404	1,015	-0.31	0.24	0.45	0.36	0.28	0.39	0.27

Model Evaluation Period											
Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.17	1,560	760	-0.45	0.19	0.39	0.42	0.32	0.22	0.20
	SG	0.39	1,510	724	-0.36	0.23	0.57	0.35	0.26	0.45	0.35
	WA	0.38	1,542	719	-0.42	0.24	0.57	0.35	0.25	0.46	0.36
MERRA	NN	0.24	1,234	686	0.09	0.27	0.45	0.38	0.30	0.35	0.25
	SG	0.22	1,301	716	-0.01	0.24	0.41	0.37	0.29	0.38	0.26
	WA	0.15	1,260	868	0.05	0.08	0.33	0.47	0.39	0.03	0.01
TRMM	NN	0.22	1,619	859	-0.54	0.10	0.31	0.53	0.38	-0.29	0.04
	SG	0.27	1,572	828	-0.47	0.12	0.42	0.42	0.33	0.20	0.17
	WA	0.28	1,609	824	-0.54	0.12	0.42	0.43	0.33	0.17	0.17

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.32: Model calibration and evaluation results[†] for Neuse - Baseflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.75	571	360	0.74	0.50	0.72	0.21	0.16	0.69	0.46
	SG	0.80	506	298	0.80	0.59	0.82	0.16	0.12	0.81	0.59
	WA	0.81	507	303	0.80	0.58	0.83	0.16	0.12	0.82	0.59
MERRA	NN	0.45	851	494	0.42	0.32	0.48	0.27	0.22	0.45	0.28
	SG	0.55	766	465	0.53	0.36	0.54	0.26	0.20	0.52	0.33
	WA	0.30	1,107	581	0.02	0.20	0.45	0.35	0.28	0.11	0.06
TRMM	NN	0.73	637	388	0.68	0.46	0.65	0.23	0.18	0.63	0.41
	SG	0.78	572	336	0.74	0.54	0.73	0.20	0.15	0.72	0.49
	WA	0.77	593	337	0.72	0.53	0.74	0.19	0.15	0.73	0.50

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	SGNN	0.56	449	280	0.54	0.45	0.68	0.23	0.18	0.66	0.46
	SG	0.75	447	275	0.54	0.46	0.81	0.21	0.16	0.71	0.51
	WA	0.76	435	253	0.56	0.50	0.82	0.20	0.15	0.75	0.55
MERRA	NN	0.50	468	307	0.50	0.39	0.65	0.24	0.19	0.62	0.41
	SG	0.43	508	343	0.41	0.32	0.57	0.26	0.21	0.57	0.35
	WA	0.45	515	417	0.39	0.18	0.57	0.34	0.29	0.22	0.12
TRMM	NN	0.49	538	345	0.33	0.32	-	-	-	-	-
	SG	0.58	499	322	0.43	0.36	0.66	0.26	0.20	0.56	0.40
	WA	0.58	511	327	0.40	0.35	0.66	0.26	0.20	0.55	0.39

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.33: Model calibration and evaluation results[†] for Ogeechee - All Flows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.71	598	373	0.64	0.39	0.48	0.35	0.27	0.34	0.24
	SG	0.65	836	334	0.29	0.45	0.78	0.23	0.17	0.73	0.53
	WA	0.76	532	293	0.72	0.52	0.70	0.25	0.20	0.66	0.45
MERRA	NN	0.32	843	509	0.28	0.17	0.38	0.39	0.31	0.18	0.13
	SG	0.32	847	505	0.28	0.18	0.39	0.39	0.31	0.18	0.12
	WA	0.32	850	509	0.27	0.17	0.40	0.40	0.32	0.15	0.11
TRMM	NN	0.56	672	383	0.54	0.38	0.53	0.31	0.23	0.49	0.35
	SG	0.63	648	378	0.58	0.38	0.54	0.32	0.25	0.44	0.31
	WA	0.66	729	398	0.47	0.35	0.47	0.36	0.27	0.32	0.26

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.71	735	403	0.68	0.53	-	-	-	-	-
	SG	0.72	1,136	536	0.23	0.38	-	-	-	-	-
	WA	0.79	808	466	0.61	0.46	0.68	0.42	0.28	0.33	0.36
MERRA	NN	0.33	1,088	690	0.29	0.20	0.28	0.49	0.38	0.06	0.13
	SG	0.36	1,062	672	0.32	0.22	0.30	0.48	0.38	0.10	0.15
	WA	0.36	1,073	678	0.31	0.22	0.30	0.49	0.38	0.08	0.15
TRMM	NN	0.61	1,084	548	0.29	0.37	0.67	0.34	0.27	0.56	0.40
	SG	0.61	1,069	585	0.31	0.32	-	-	-	-	-
	WA	0.62	1,581	753	-0.50	0.13	-	-	-	-	-

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.34: Model calibration and evaluation results[†] for Ogeechee - Stormflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.65	514	279	0.57	0.38	0.25	0.58	0.41	-0.07	0.10
	SG	0.55	763	281	0.07	0.37	0.57	0.40	0.28	0.46	0.36
	WA	0.70	471	232	0.64	0.48	0.45	0.44	0.31	0.36	0.32
MERRA	NN	0.30	666	360	0.28	0.19	0.29	0.55	0.42	0.02	0.06
	SG	0.30	671	358	0.27	0.20	0.28	0.57	0.43	-0.07	0.04
	WA	0.30	674	362	0.27	0.19	0.28	0.58	0.43	-0.08	0.03
TRMM	NN	0.50	567	306	0.48	0.31	0.34	0.50	0.37	0.21	0.18
	SG	0.56	560	295	0.49	0.34	0.37	0.49	0.35	0.23	0.22
	WA	0.58	635	311	0.35	0.30	0.35	0.49	0.36	0.22	0.20

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.61	640	330	0.57	0.45	0.40	0.66	0.42	-0.37	0.11
	SG	0.59	987	438	-0.01	0.28	0.69	0.44	0.32	0.39	0.33
	WA	0.69	670	347	0.52	0.42	0.53	0.56	0.38	0.02	0.20
MERRA	NN	0.29	831	488	0.26	0.18	0.26	0.57	0.45	0.00	0.06
	SG	0.31	819	480	0.28	0.19	0.27	0.56	0.45	0.01	0.07
	WA	0.31	826	484	0.27	0.18	0.27	0.57	0.45	-0.01	0.07
TRMM	NN	0.46	971	439	0.00	0.26	0.51	0.46	0.36	0.34	0.26
	SG	0.47	918	473	0.14	0.23	0.50	0.56	0.41	0.02	0.16
	WA	0.49	1,315	571	-0.77	0.07	0.52	0.50	0.37	0.22	0.24

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

Table 4.35: Model calibration and evaluation results[†] for Ogeechee - Baseflows.

Model Calibration Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.82	153	120	0.75	0.45	0.57	0.27	0.21	0.51	0.35
	SG	0.87	170	98	0.70	0.55	0.87	0.16	0.12	0.83	0.63
	WA	0.88	119	84	0.85	0.61	0.81	0.18	0.14	0.79	0.57
MERRA	NN	0.39	254	180	0.33	0.17	0.42	0.34	0.27	0.26	0.18
	SG	0.39	255	178	0.32	0.18	0.43	0.34	0.27	0.25	0.18
	WA	0.39	257	179	0.31	0.17	0.43	0.34	0.27	0.23	0.16
TRMM	NN	0.69	176	110	0.68	0.49	0.64	0.24	0.17	0.63	0.48
	SG	0.74	165	112	0.71	0.48	0.60	0.27	0.20	0.52	0.39
	WA	0.80	179	122	0.66	0.43	0.52	0.31	0.22	0.37	0.32

Model Evaluation Period

Input Method [‡]		Linear Model					Logarithmic Model				
		R ²	RMSE	MAE	NSE	mNSE	R ²	RMSE	MAE	NSE	mNSE
Ground	NN	0.84	181	119	0.82	0.63	-	-	-	-	-
	SG	0.92	288	183	0.53	0.43	-	-	-	-	-
	WA	0.93	223	159	0.72	0.50	0.76	0.34	0.23	0.53	0.47
MERRA	NN	0.38	344	242	0.34	0.25	0.28	0.47	0.35	0.10	0.18
	SG	0.43	331	230	0.39	0.28	0.32	0.46	0.34	0.14	0.20
	WA	0.43	336	231	0.37	0.28	0.31	0.46	0.35	0.12	0.20
TRMM	NN	0.87	234	161	0.69	0.50	0.78	0.28	0.21	0.68	0.51
	SG	0.81	291	182	0.53	0.43	-	-	-	-	-
	WA	0.82	460	275	-0.18	0.15	-	-	-	-	-

[†] RMSE is root mean squared error, MAE is mean absolute error, NSE is Nash-Sutcliffe Efficiency, mNSE is modified Nash-Sutcliffe Efficiency

[‡] NN is nearest neighbor method, SG is segmented method, WA is weighted average method.

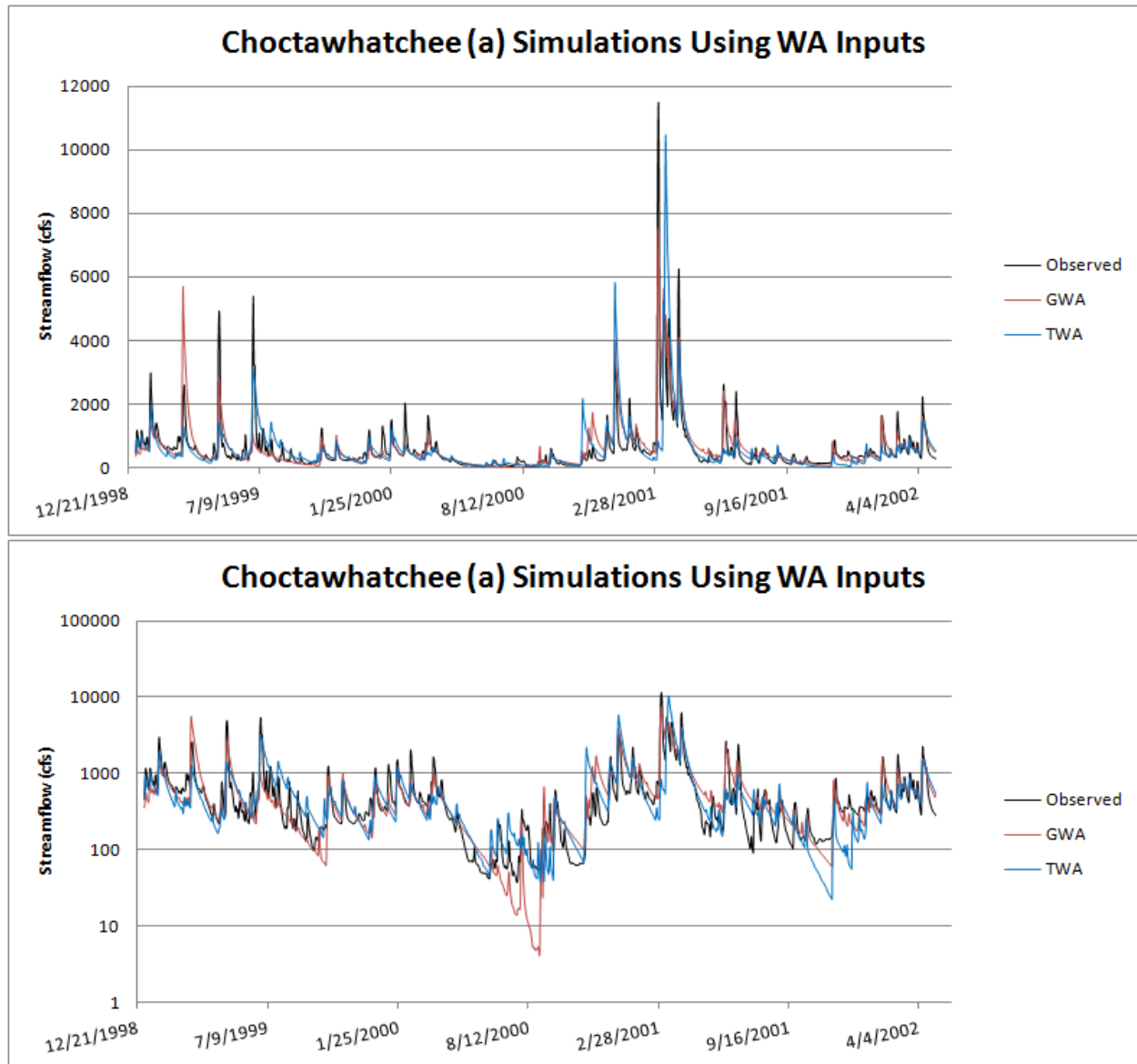


Figure 4.1: Selected results for the Choctawhatchee(a) watershed model using watershed averaged inputs (WA), linear scale (top) and logarithmic scale (bottom).

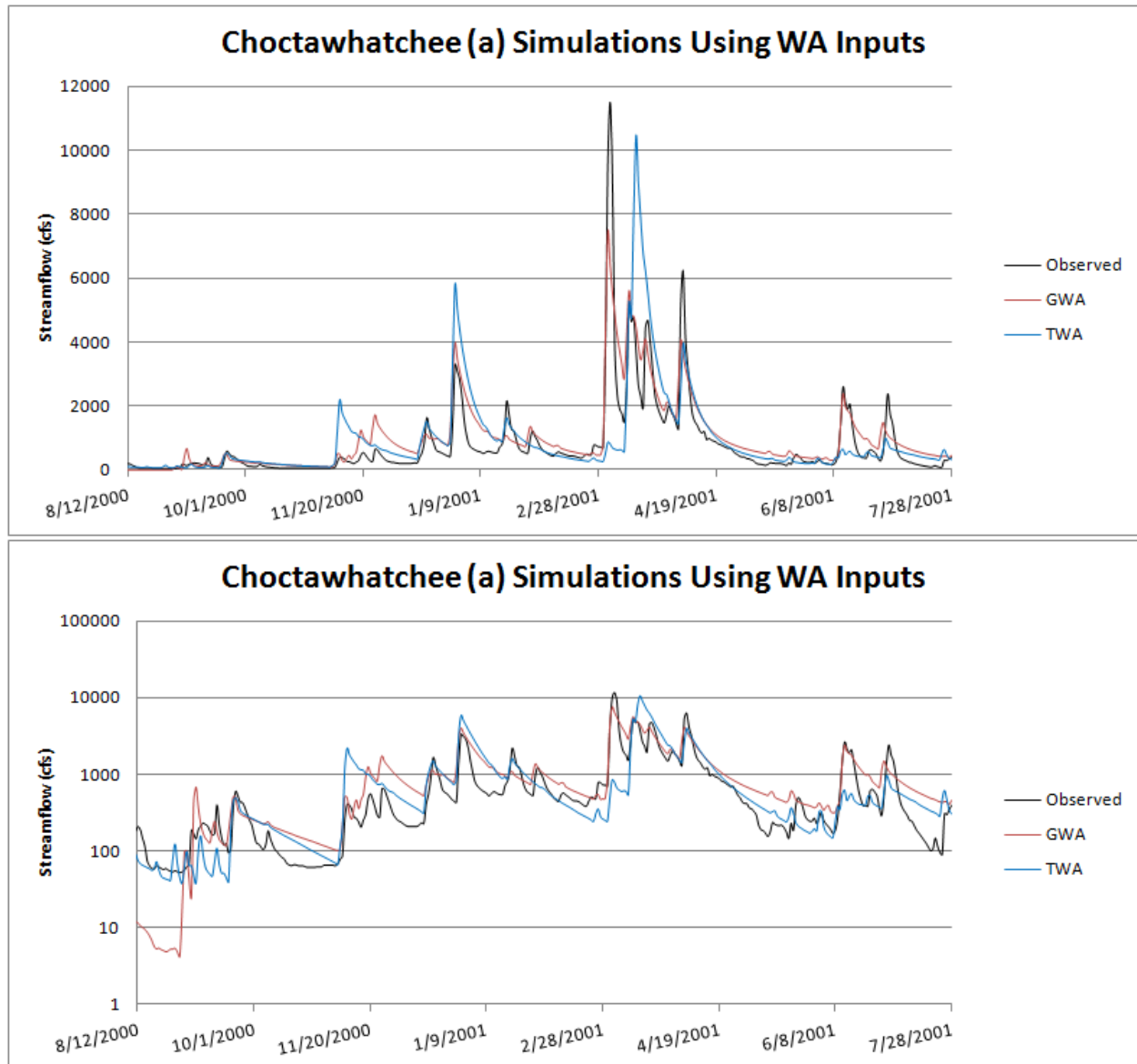


Figure 4.2: Selected results for the Choctawhatchee(a) watershed model using watershed averaged inputs (WA), linear scale (top) and logarithmic scale (bottom).

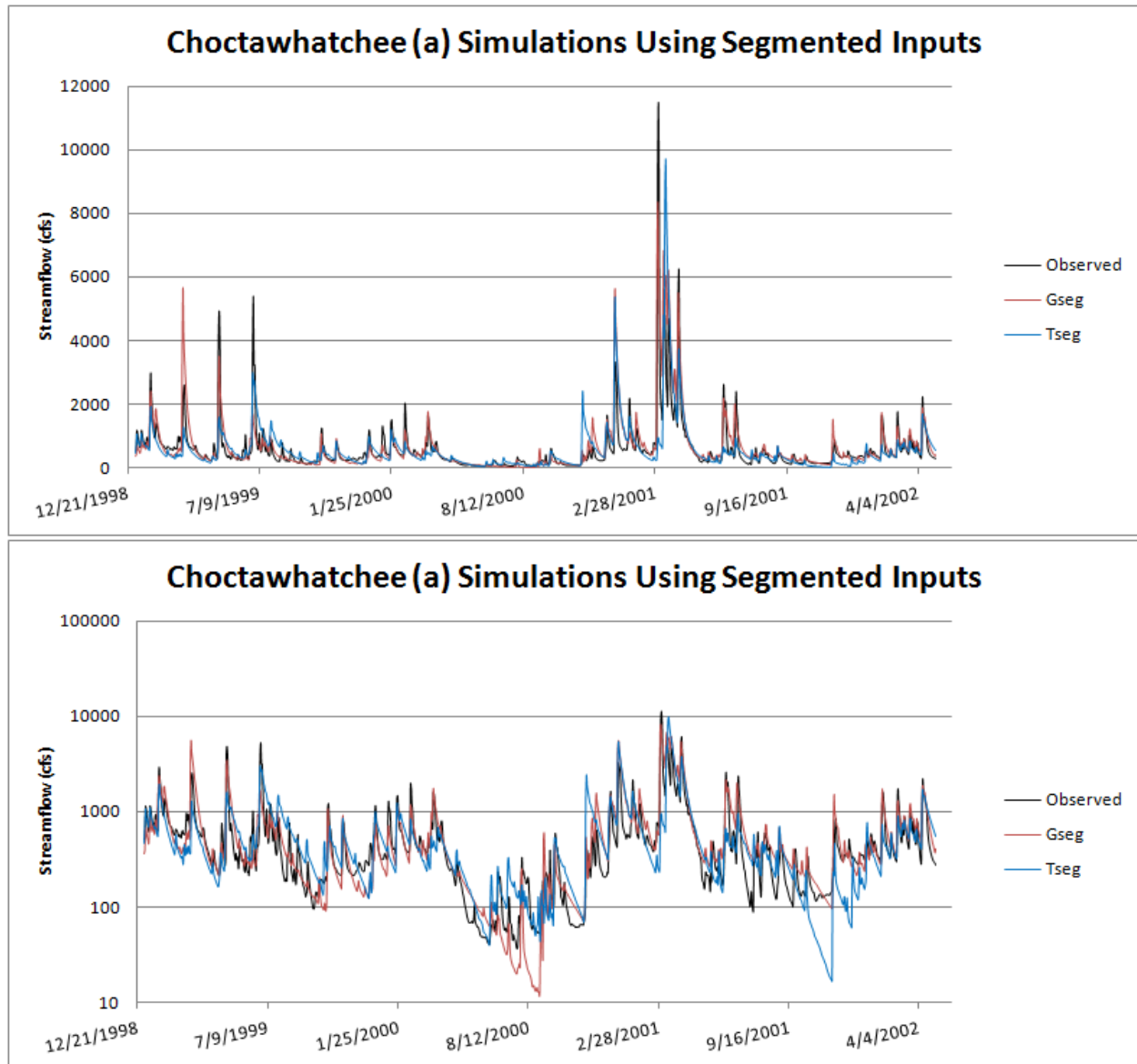


Figure 4.3: Selected results for the Choctawhatchee(a) watershed model using segmented inputs (SG), linear scale (top) and logarithmic scale (bottom).

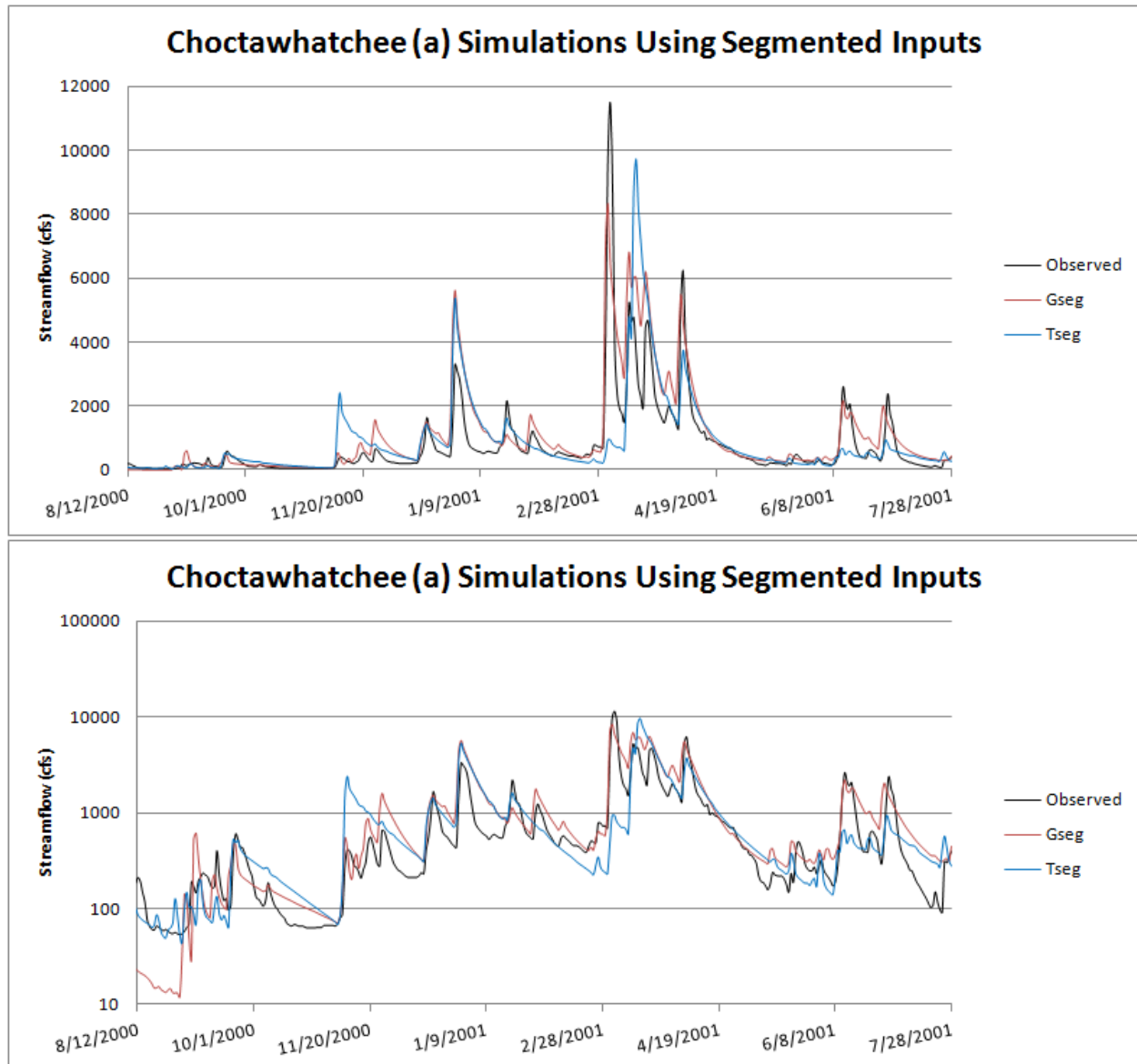


Figure 4.4: Selected results for the Choctawhatchee(a) watershed model using segmented inputs (SG), linear scale (top) and logarithmic scale (bottom).

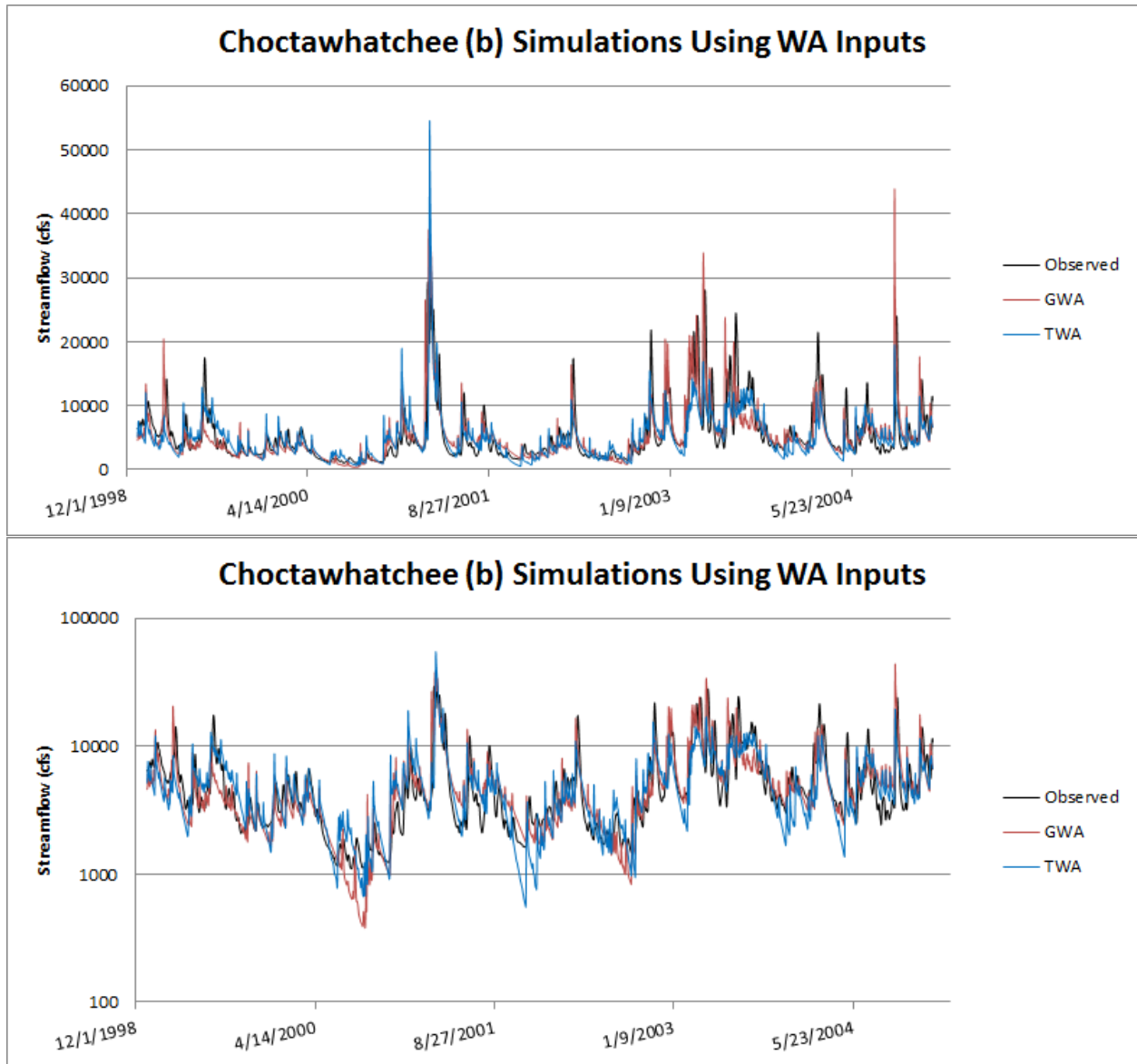


Figure 4.5: Selected results for the Choctawhatchee(b) watershed model using watershed averaged inputs (WA), linear scale (top) and logarithmic scale (bottom).

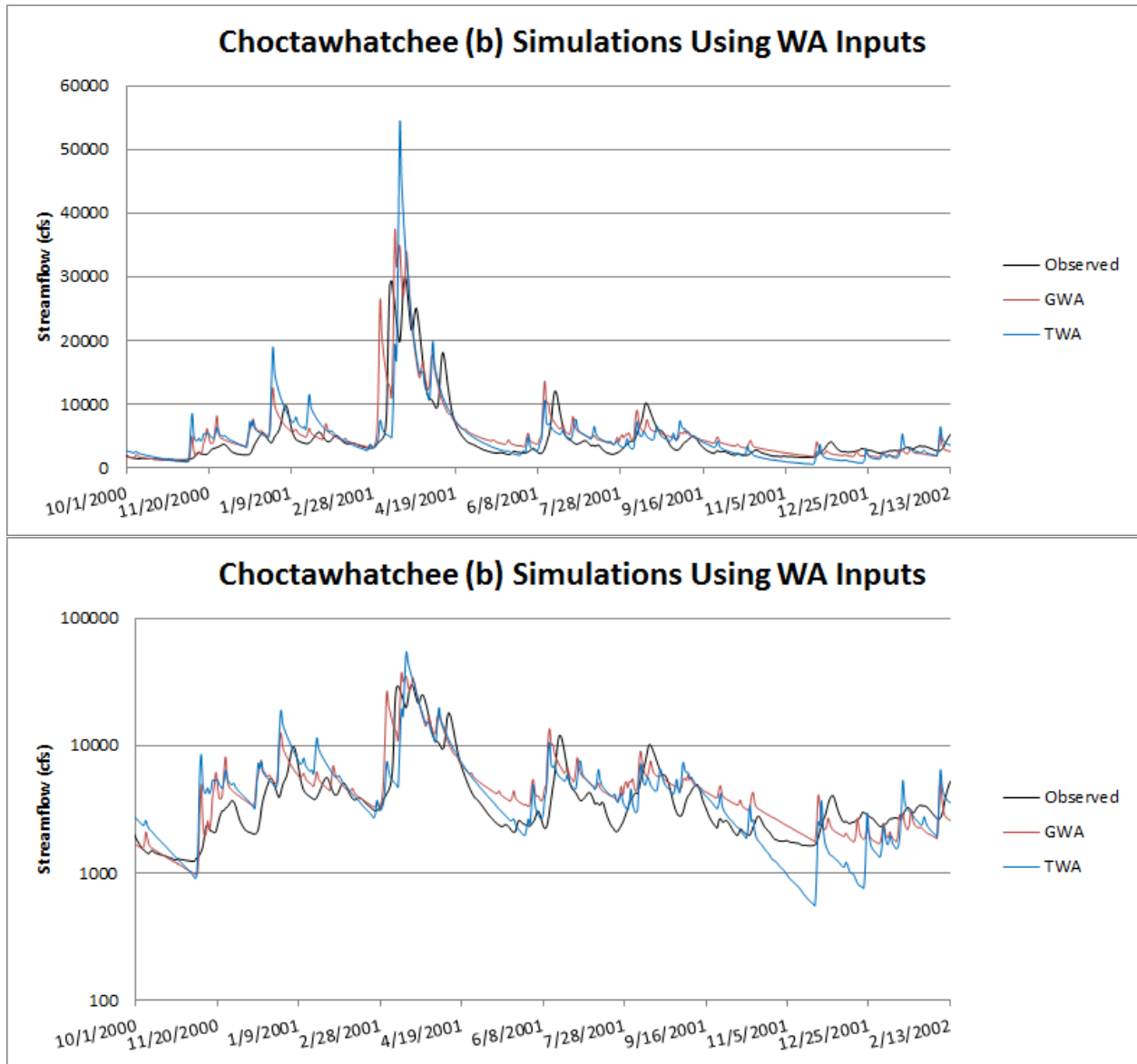


Figure 4.6: Selected results for the Choctawhatchee(b) watershed model using watershed averaged inputs (WA), linear scale (top) and logarithmic scale (bottom).

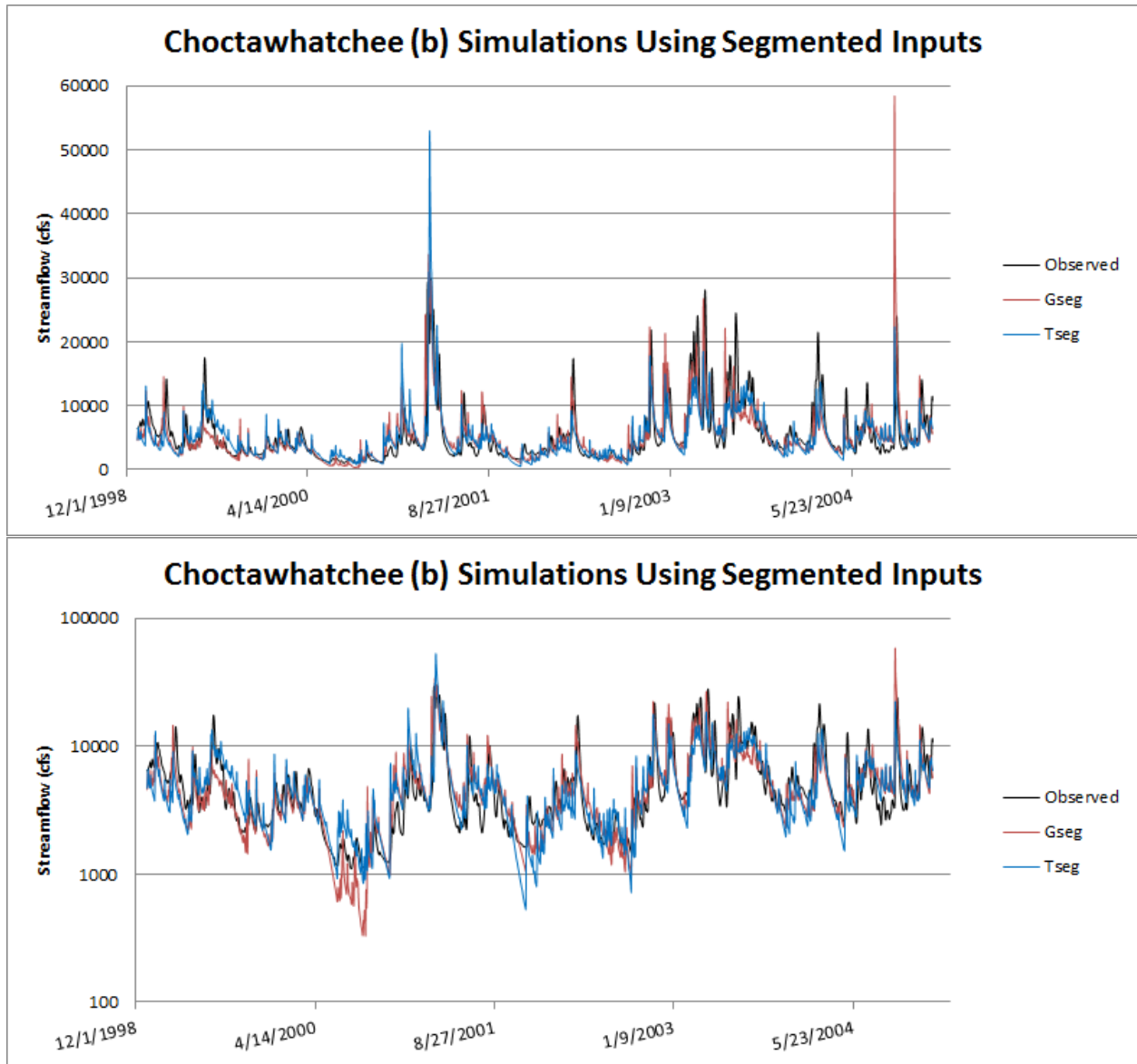


Figure 4.7: Selected results for the Choctawhatchee(b) watershed model using segmented inputs (SG), linear scale (top) and logarithmic scale (bottom).

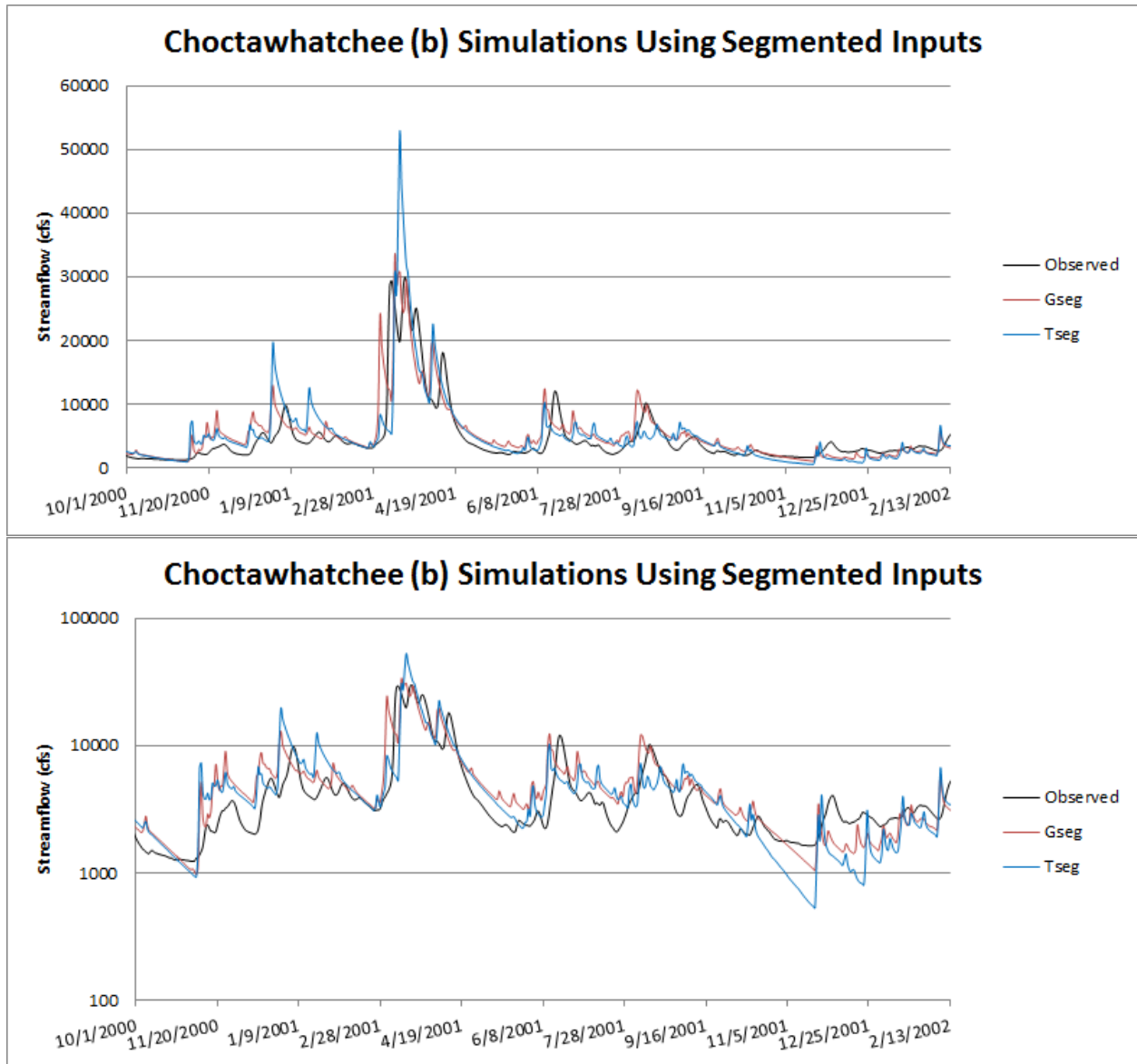


Figure 4.8: Selected results for the Choctawhatchee(b) watershed model using segmented inputs (SG), linear scale (top) and logarithmic scale (bottom).

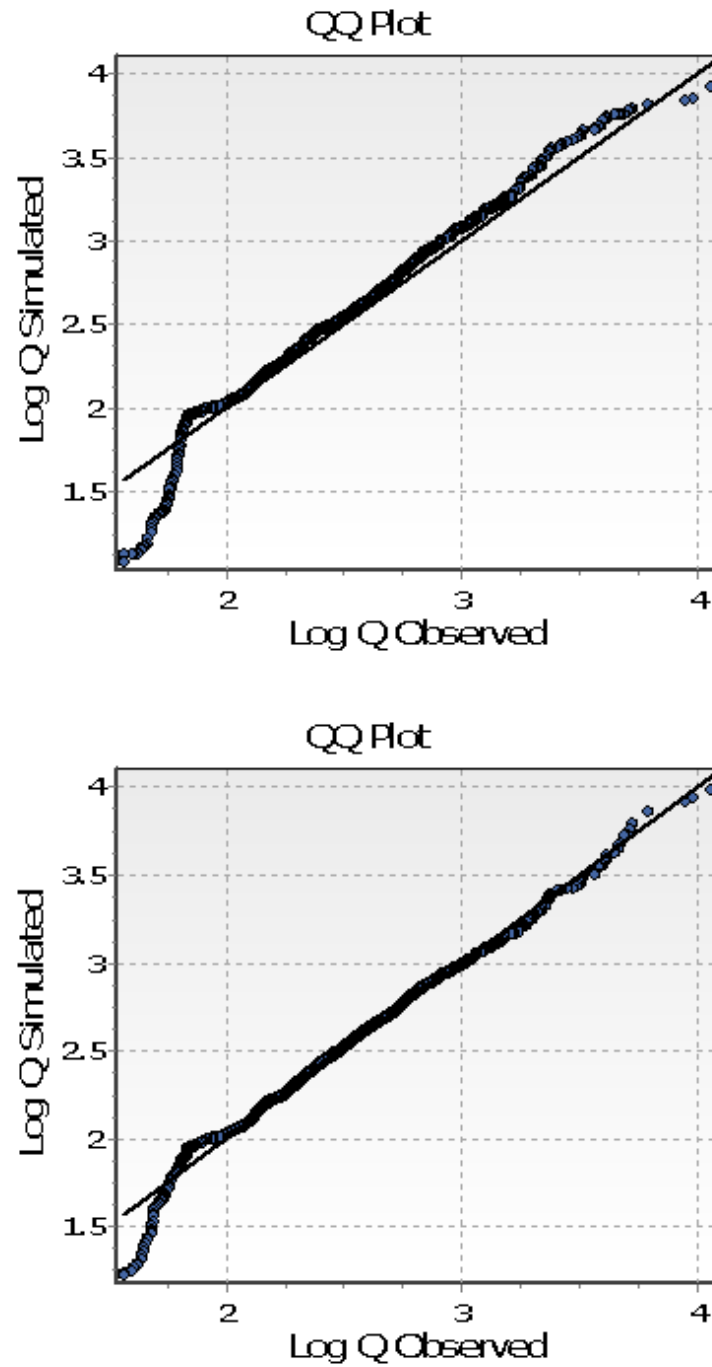


Figure 4.9: Q-Q plots for the Choctawhatchee(a) watershed model using segmented (SG), ground-based inputs (top) and remotely-sensed inputs (bottom).

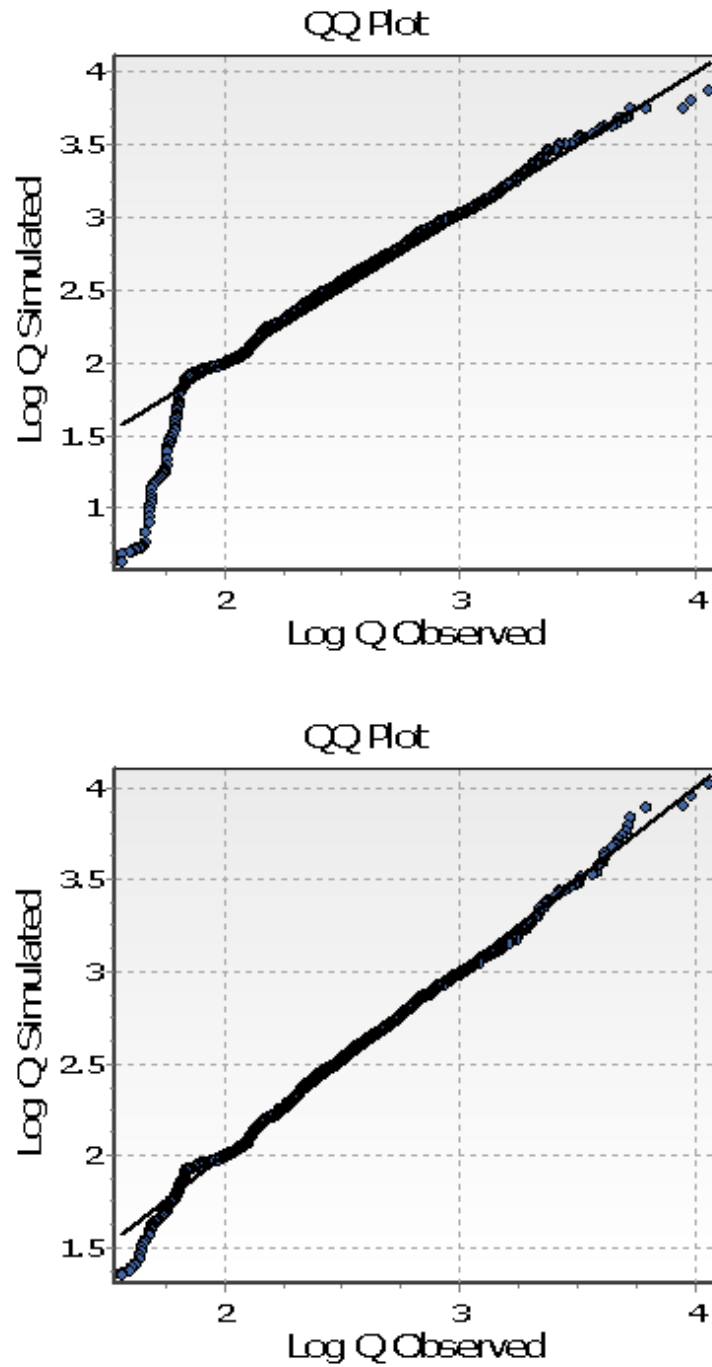


Figure 4.10: Q-Q plots for the Choctawhatchee(a) watershed model using areally weighted (WA), ground-based inputs (top) and remotely-sensed inputs (bottom).

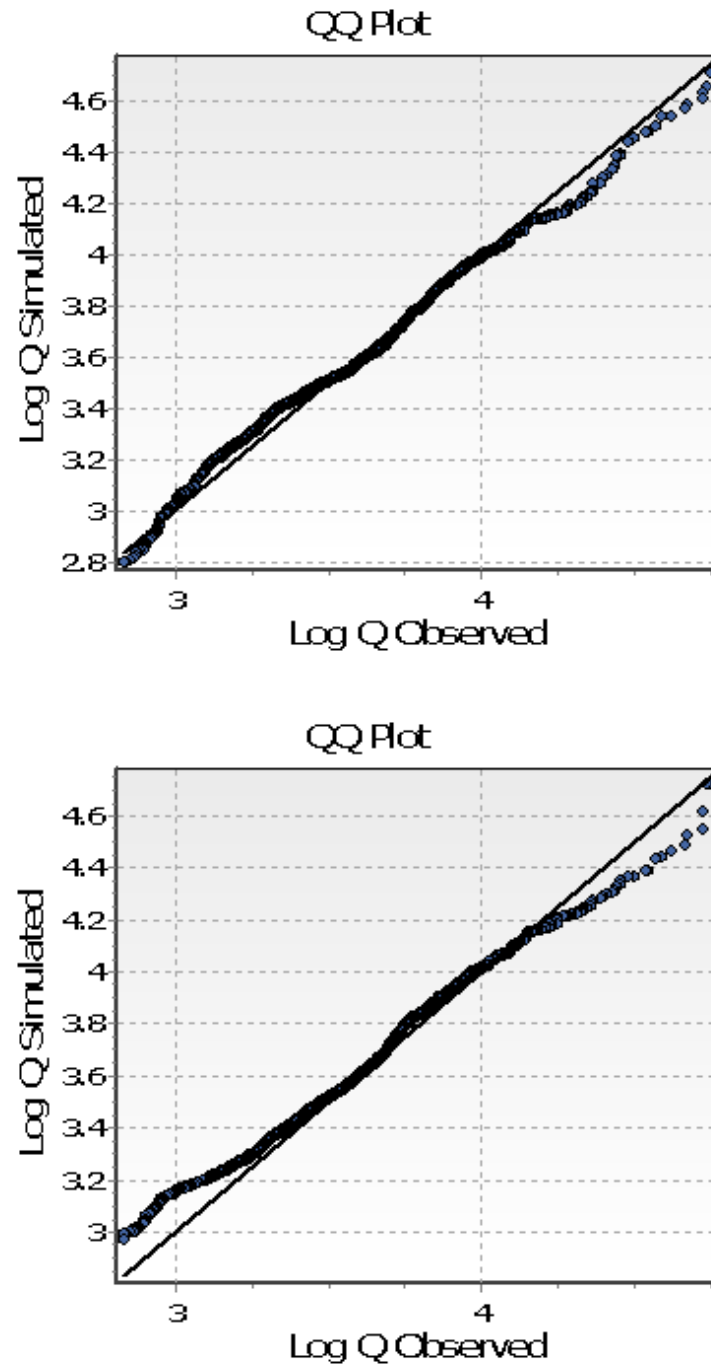


Figure 4.11: Q-Q plots for the Choctawhatchee(b) watershed model using segmented (SG), ground-based inputs (top) and remotely-sensed inputs (bottom).

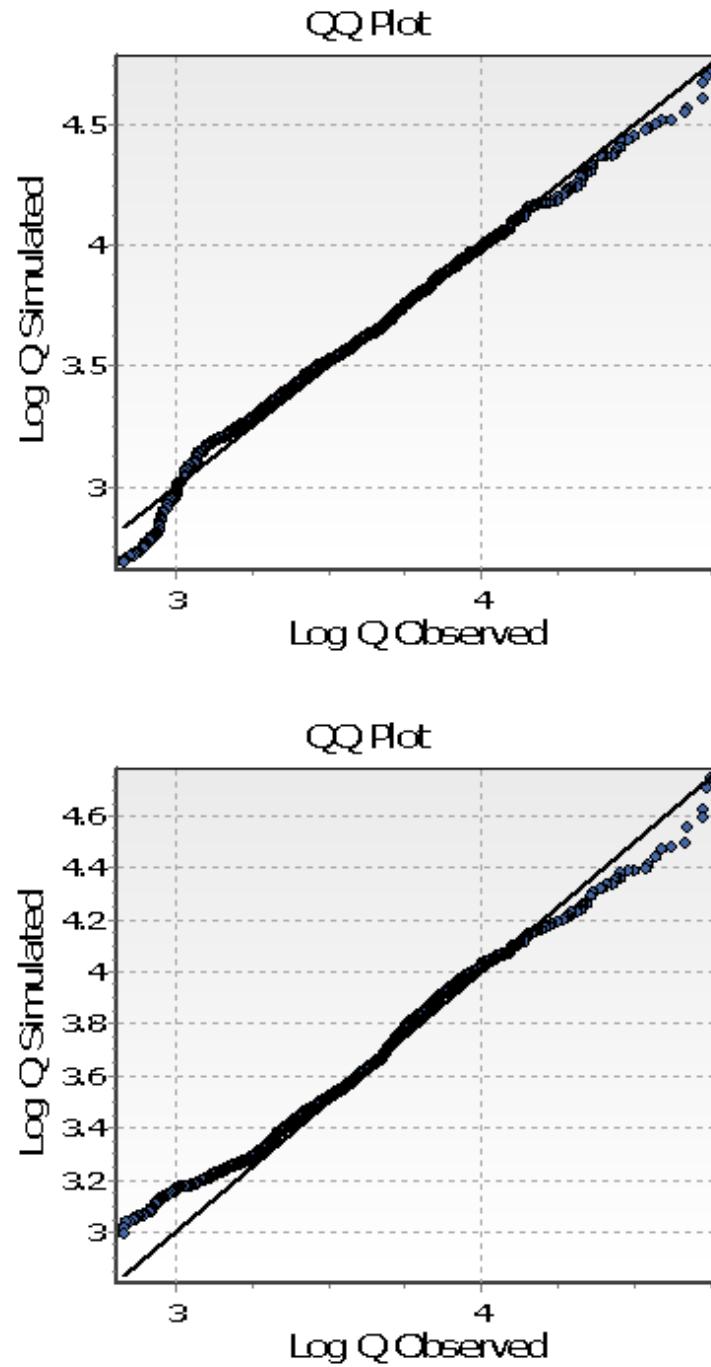


Figure 4.12: Q-Q plots for the Choctawhatchee(b) watershed model using areally weighted (WA), ground-based inputs (top) and remotely-sensed inputs (bottom).

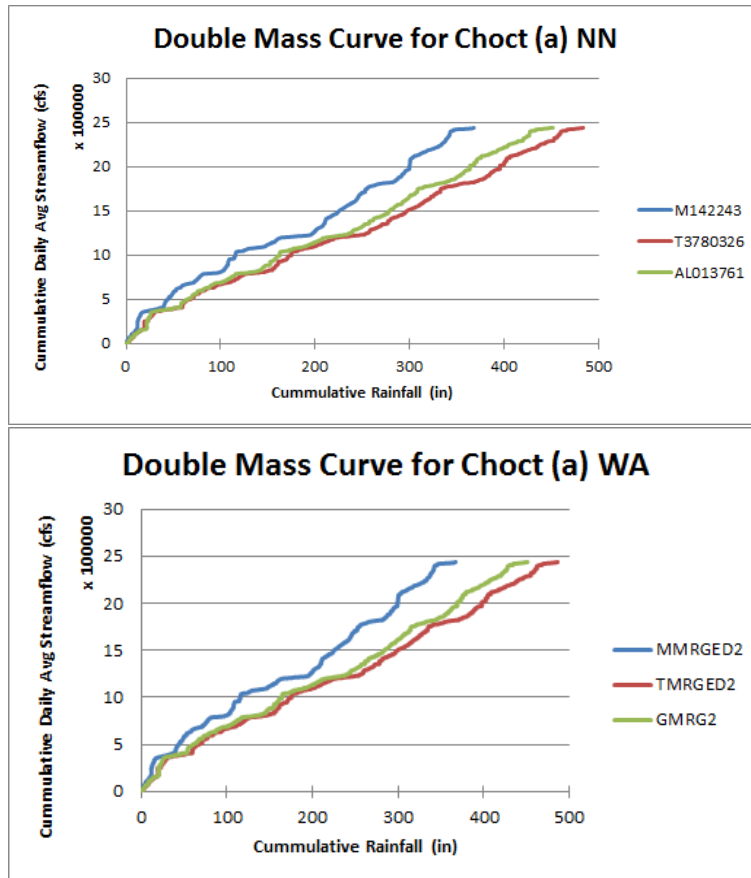


Figure 4.13: Double mass curves for the Choctawhatchee(a) watershed model using TRMM, MERRA, and ground-based products, Nearest Neighbor (top) and Weighted Average (bottom).

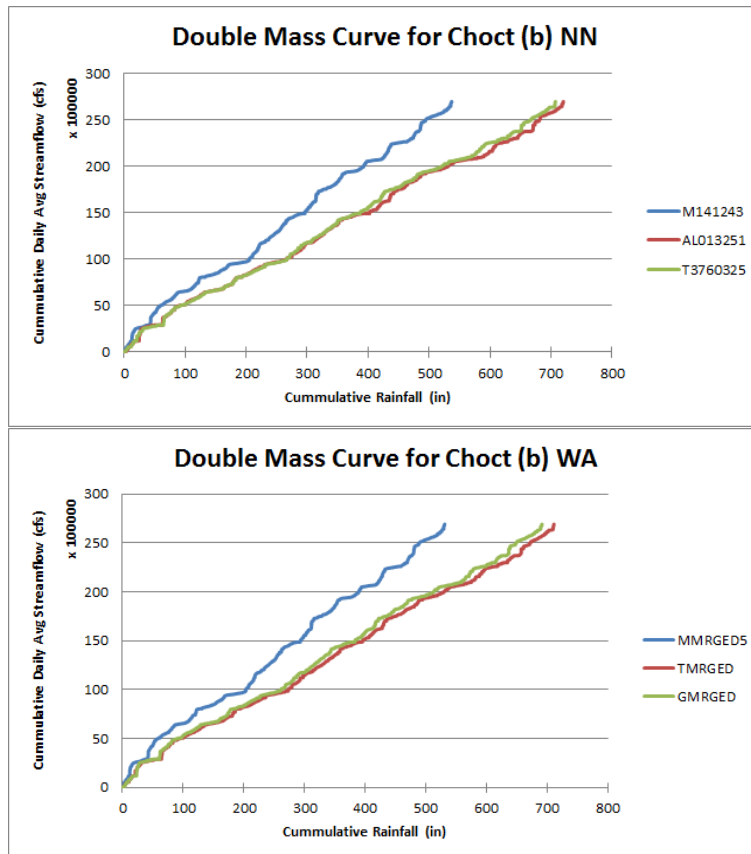


Figure 4.14: Double mass curves for the Choctawhatchee(b) watershed model using TRMM, MERRA, and ground-based products, Nearest Neighbor (top) and Weighted Average (bottom).

Chapter 5

Discussion

As noted previously, our goal has been to evaluate the suitability of using remotely sensed meteorologic data as a substitute for ground-based observations as inputs to hydrologic models. We now use the results from the previous chapter to perform this evaluation.

5.1 Visual Assessments

Time Series Analysis

Graphic presentation can be used to assess the overall quality of simulations, and many decision makers use this approach to gauge the quality of model performance. Time series were presented in the previous chapter, and both ground and TRMM driven models provide visually similar predictions during low flow conditions, although ground driven scenarios seem to capture storm events better.

It is noted that for both WA and SG inputs in the Choctawhatchee(a) model, TRMM completely misses the largest observed storm event in the series (3/3/2001-3/12/2001). Both ground and TRMM driven models severely underestimate low flow during 10/08/2001-

12/25/2001. During 6/19/2000 - 8/21/2000 ground based data highly underestimates streamflow, up to an order of magnitude at its worst.

For the Choctawhatchee(b) watershed, both ground and TRMM driven scenarios overpredict the highest flows and underpredict the lowest flows, but TRMM overprediction is reduced for the SG input. Both ground and TRMM driven models severely underestimate low flow during 10/17/2001 - 12/25/2001, but the TRMM scenarios are more pronounced.

Though it is difficult to state which model performed best using graphical interpretation alone, it seems that the graphs agree with the statistical analysis. TRMM driven scenarios are noticeably better for Choctawhatchee(b) than for Choctawhatchee(a). The graphs also illustrate that ground-based scenarios are far from perfect and TRMM scenarios do reasonably well against them, even for smaller watersheds.

Q-Q Analysis

Model performance can also be evaluated for different scenarios by comparing the calibrated model to observed streamflow data over a range of discharges. The types of scenarios examined include the type of input precipitation datasets (e.g. ground-based, TRMM MPA, MERRA) as well as the data input method (e.g. by watershed segment, areally weighted average, segmenting grid cell).

The Q-Q plots for all Choctawhatchee(a) scenarios (presented in the previous chapter) show that the lowest flows were underestimated, especially for ground-based scenarios. Ground-based scenarios also under-predicted high flows, whereas TRMM-based scenarios over-predicted. Interestingly, high stormflows return to the 1:1 line for both TRMM-based scenarios.

The Q-Q plot for Choctawhatchee(b) ground-based WA scenario shows that the lowest flows were underestimated. Choctawhatchee(b) ground-based SG scenario did well in simulating low flows, falling very close to the 1:1 line. Both Choctawhatchee(b) TRMM-based

scenarios overpredicted low flows. All scenarios for the Choctawhatchee(b) watershed underpredicted high flows. Interestingly, extremely high stormflows seem to fall back to the 1:1 line for all Choctawhatchee(b) scenarios.

Double Mass Curves

To examine the integrity of the input data, double mass curves were generated to identify systematic bias in precipitation values. By examining how the linear relationship between cumulative precipitation and cumulative streamflow, we can determine if there are any systematic errors introduced over the calibration period.

The high R^2 values along with the small slope values, representing the constant of proportionality (Searcy et al. 1960), of the regression lines suggest that there are no significant changes in the relationship between the precipitation sources and the streamflow data over the periods modeled (Table 4.3).

Visually, the double mass curves agree with the regression line, suggesting that there were no breaks in the curve due to other factors, such as land use and climate changes in the areas. All four scenarios in the Choct (a) and Choct (b) watersheds show consistent behavior throughout the span of the modeled time series. For all four scenarios, MERRA under predicts precipitation volumes compared to TRMM and ground-based stations.

5.2 Statistical Measures

Satellite-Derived vs Ground Based Inputs

The overall results of the residual standard error ratios (Table 4.2) show that TRMM Version 7 performs well compared to ground inputs, but varies with watershed scale. The TRMM and MERRA driven models perform more poorly than weather station data for the two

smallest watersheds, Choctawhatchee(a) (2,315 km²) and Ogeechee (3,419 km²), in every scenario.

Choctawhatchee(a) and Ogeechee scenarios performed the worst with MERRA inputs (Calibration: MERRA: 2.0 - 2.6; Evaluation: MERRA: 2.2 - 2.7 and Calibration: MERRA: 1.6 - 2.5; Evaluation: MERRA: 2.7 - 3.2 respectively). TRMM scenarios performed better than MERRA inputs for both models (Calibration: TRMM: 1.1 - 1.3; Evaluation: TRMM: 1.2 - 1.6 and Calibration: TRMM: 1.5 - 1.6; Evaluation: TRMM: 1.4 - 1.5 respectively) but still fail to achieve the fit ground-based scenarios produced.

For the Neuse model (6,084 km²), which has a drainage area nearly double the Ogeechee model, satellite-driven scenarios perform more or less equally to weather station data (Calibration: MERRA: 0.6 - 0.8, TRMM: 0.9 - 1.3; Evaluation: MERRA: 0.8 - 1.3, TRMM: 1.1 - 1.3).

It should be noted that for the Neuse watershed, MERRA actually produces the best results for all scenarios in the calibration period and all except the MERRA WA scenario (1.3) in the evaluation period.

Choctawhatchee(c) (9,125 km²) and Clyo (9,127 km²) produce similar results to ground-based for TRMM driven scenarios (Calibration: TRMM: 0.8 - 1.1; Evaluation: TRMM: 0.8 - 1.2 and Calibration: TRMM: 1.0 for all; Evaluation: TRMM: 1.0 - 1.2 respectively)).

Choctawhatchee(c) TRMM scenarios achieve better calibration than ground-based data for some scenarios (TRMM NN- 0.8 and TRMM WA- 0.9 during calibration and TRMM SG- 0.8 during evaluation). Choctawhatchee(c) scenarios using MERRA data perform poorly compared to ground-based data in the calibration and evaluation periods (Calibration: MERRA: 1.1 - 1.9; Evaluation: MERRA: 1.1 - 1.4), except MERRA NN during calibration (1.1) and MERRA SG during evaluation(1.1).

Clyo MERRA driven scenarios perform well over both the calibration and evaluation periods with equal or near equal performance with ground-based data (Calibration: MERRA:

1.0 - 1.2; ; Evaluation: MERRA: 0.9 for all). For the evaluation period, MERRA driven Clyo scenarios actually perform better than ground based inputs (MERRA NN- 0.9, MERRA SG- 0.9, MERRA WA- 0.9).

Choctawhatchee(b) (11,406 km²), the largest of the six watersheds, shows better results using TRMM driven data (Calibration: TRMM: 0.8 - 0.9; Evaluation: TRMM: 0.8 - 1.0). Choctawhatchee(b) MERRA driven scenarios perform well over both the calibration and evaluation periods with equal or near equal performance with ground-based data (Calibration: MERRA: 0.9 - 1.1; Evaluation: MERRA: 1.0 for all). TRMM driven scenarios outperform ground-based data in all scenarios over calibration and evaluation periods except for TRMM NN during the evaluation period (1.0).

Additional statistics show a slightly different picture than the residual standard error ratios. Table 5.1 shows the best of the nine scenarios based on the results from R², RMSE, MAE, NSE, and mNSE for the overall model runs. The input methods are not considered here, only the data source with the best metrics for each of the nine scenarios. For the majority of the simulations, ground-based data produces the best metrics. The Choctawhatchee(b) and (c) models were the only ones to produce equal or superior metrics with remotely sensed data.

Modeled drainage basin ranged from 2,315 km² (Choctawhatchee(a)) to 11,406 km² (Choctawhatchee(b)). Over all drainage sizes, ground-based data produced satisfactory results, having the best simulations for almost every simulation. Analysis of the overall model results suggest that as the basin scale increases, TRMM produces results closer to ground based data and actually out performs it in the largest watershed for both SG and areally weighted input methods.

Input Method Performance

For each input method (NN, SG, and WA) simulations are compared against observed flow over a calibration and evaluation period. The simulations were further broken into stormflow and baseflow and the logs of each of these were taken as well. Table 5.1 summarizes the information presented in the previous chapter to show the best products for each watershed.

Results from the input method show that SG models produce overall better fitting simulations for both the calibration and evaluation periods across all watershed scales. The merged input models also do very well, especially with TRMM precipitation data. This is interesting because both input methods have unique qualities. SG models consist of an extra ten parameters for each segment. Extra parameters add degrees of freedom to the inverse least squares problem solved in calibration and increase calibration run time as well as further parameterize the model.

Another downside to SG models is that, unlike the merged models, the complete input dataset is not used. SG models would be most beneficial when modeling large scale watersheds that span over multiple climatic regions.

The merged model requires a significant amount of input data to produce. Areally weighting is easy to employ and the calibration run time is conservative because it only consists of a single input. The SG model seems to produce the best model calibrations, but is costly in set up time and numerical stability in calibration. Using the merged input method reduces the computational burden during calibration and includes all available input data.

NN input models performed the poorest as expected. This input method is best suited for areas with limited or unavailable input datasets and small watersheds. Only the SG and merged models will be considered from here. They will be analyzed as two separate groups so that patterns between scale and input produces can be evaluated by method.

Percent bias (PBIAS) was calculated for each of the scenarios of the six watersheds. For most scenarios, ground based and TRMM based input scenarios performed well for all watersheds. PBIAS remained under 10 percent for all but a few of the ground and TRMM based scenarios and under five percent for all Neuse and Clyo scenarios during the calibration period. MERRA based scenarios did not perform as well during the calibration period, except for Clyo and Ogeechee scenarios, having as high as 48.8 PBIAS for the Neuse areally weighted scenario.

During the evaluation period, PBIAS rose for all scenarios, though TRMM and ground based still fall under ten percent for select scenarios (Choctawhatchee(a) Grnd NN (-1.2) and SG (3.5); Choctawhatchee(b) Grnd SG (-7.7) and WA (1.4); Choctawhatchee(b) TRMM SG (-9.2) and WA (-9.0); Choctawhatchee(c) Grnd NN (4.9), SG (-0.9) and WA (-2.8); Choctawhatchee(c) TRMM NN (-0.3), SG (7.3) and WA (4.7); Clyo Grnd NN (0.1), SG (-2.9) and WA (-2.9); Clyo TRMM NN (-6.8), SG (-7.0) and WA (-5.7); Neuse MERRA NN (7.2) and SG (0.82); Neuse TRMM NN (-9.2)). Clyo consistently had low PBIAS for all scenarios during both the calibration (Grnd: -2.6 to -0.9; MERRA: 3.2 to 3.7; TRMM -1.3 to -1.7) and evaluation (Grnd: -2.9 to 0.1; MERRA: 10.4 to 10.6; TRMM -7.0 to -5.7) periods. This is interesting, considering that it is also the only watershed with reservoir inflow.

Singh et. al. (2005) suggests using the ratio of the RMSE to the standard deviation of measured data (RSR) to standardize the RMSE because it standardizes the RMSE with the standard deviation of the observed dataset. By scaling or normalizing the error index statistic (RMSE) a standard or index can be defined as a threshold for an "acceptable" model simulation.

Moriasi et al. (2007) suggest an index for classifying monthly streamflow simulations to observations. This index was relaxed to compare daily data. For this study, an RSR value lower than 0.8 was considered a satisfactory model performance for any particular scenario. The outcome was consistent with PBIAS patterns, except in a few situations

(Choctawhatchee(a) Grnd SG (PBIAS: -15.2, RSR: 0.58) calibration; Choctawhatchee(a) Grnd WA (PBIAS: 15.9, RSR: 0.72) evaluation; Choctawhatchee(a) TRMM NN (PBIAS: -4.0, RSR: 0.93; PBIAS: 13.3, RSR: 0.75), SG (PBIAS: 0.8, RSR: 1.48; PBIAS: 15.2, RSR: 0.76) and WA (PBIAS: 0.5, RSR: 0.88); PBIAS: 16.1; RSR: 0.77) calibration and evaluation; Choctawhatchee(b) Grnd NN (PBIAS: 18.8, RSR: 0.77) evaluation; Clyo MERRA NN (PBIAS: 10.6, RSR: 0.69), SG (PBIAS: 10.5, RSR: 0.69) and WA (PBIAS: 10.4, RSR: 0.69) evaluation; Neuse MERRA SG (PBIAS: 14.0, RSR: 0.79) calibration; Neuse TRMM NN (PBIAS: 3.6, RSR: 0.92), SG (PBIAS: 0.5, RSR: 0.85), WA (PBIAS: 1.5, RSR: 0.89) calibration; Neuse MERRA NN (PBIAS: 7.2, RSR: 0.84) and SG (PBIAS: 8.2, RSR: 0.90) evaluation; Neuse TRMM NN (PBIAS: -9.2, RSR: 1.05) evaluation; Ogeechee MERRA NN (PBIAS: -0.7, RSR: 0.85) and SG (PBIAS: 0.8, RSR: 0.85) calibration; Ogeechee TRMM WA (PBIAS: -13.4, RSR: 0.73) calibration; Ogeechee Grnd NN (PBIAS: -11.5, RSR: 0.57) and WA (PBIAS: -36.1, RSR: 0.63) evaluation; Ogeechee MERRA NN (PBIAS: -14.6, RSR: 0.72) evaluation).

For TRMM-driven Choctawhatchee(a), values exceeded 0.8 (1.48 for SG) for all scenarios during the calibration period, where PBIAS values were all below five percent. The evaluation period for TRMM driven Choctawhatchee(a) was the opposite, where RSR values met the 0.8 criteria, but PBIAS exceeded 10 percent. RSR was also consistently low (Calibration: 0.66 - 0.73; Evaluation: 0.67 - 0.73) for all Clyo scenarios.

Baseflow Separation Metrics

Both areally weighted and segmented scenarios for all six models showed similar patterns between simulations. Stormflow simulations reduced RMSE and MAE but increased NSE and R^2 compared to the overall model simulations. Baseflow simulations significantly reduced all metrics compared to both overall model flow and stormflow. The results were the same for both calibration period and evaluation period and for all products and input methods.

The exception was for the three Choctawhatchee models driven with MERRA data, where NSE and mNSE of the overall model run was better than stormflow and baseflow simulations for all cases.

This was expected because R^2 , NSE, and mNSE used for statistical analysis are highly influenced by large values. By filtering the high flows from the low flows, MAE and RMSE are reduced between for each dataset and they become more homoscedastic in nature. This is important to show because it illustrates the point that using appropriate statistics to evaluate the model performance is as important as choosing the appropriate input product and hydrologic model. Depending on what portion of the simulation you are concerned with, makes a difference on the metrics that should be used to evaluate the performance.

Log-Scale Metrics

For all models, model flow produced better results, meaning higher R^2 , NSE, and mNSE values and lower RMSE and MAE values, than stormflow. Baseflow produced better results, meaning higher R^2 , NSE, and mNSE values and lower RMSE and MAE values, than overall model simulations for logged values. Exceptions were MERRA driven scenarios for Choctawhatchee(a) during the evaluation period, and Choctawhatchee(b and c) during the calibration period, where NSE and mNSE were negative values and much lower compared to both stormflow and baseflow values.

It was expected that model flow would improve because log-transformed data exhibit homoscedastic behavior, thus minimizing the influence of outliers on evaluations statistics. The comparison between overall logged model flow and logged baseflow and storm flow shows interesting patterns. The results suggest that if a study is concerned with high flows, it may be better to use the logged overall model flow as opposed to stormflow alone. Additionally, separating the baseflow after taking the logarithm further improves the fit between observed and simulated flows.

Effects of Physical Characteristics

Watersheds used in this study varied in drainage basin size, land cover, and proportion of physiographic region. These factors were compared to results to determine if any significant patterns were discernible. Physiographic region affects hydrology in different ways, making it difficult to determine how percent physiographic region affects output simulations given the variability in other factors such as land cover and drainage basin size.

However, Choctawhatchee(c) (9,125 km²) and Clio (9,127 km²) watersheds, which are very similar in size and land cover, differ in percent physiographic province (100 percent Coastal Plain and 73 percent Coastal Plain respectively). Between these models, there is no clear evidence that one watershed is modeled better based on physiographic province alone:

- Choctawhatchee(c) Calibration: MERRA NN- 1.1, MERRA SG- 1.9, MERRA WA- 1.5, TRMM NN- 0.8, TRMM SG- 1.1, TRMM WA- 0.9;
- Clio Calibration: MERRA NN- 1.0, MERRA SG- 1.1, MERRA WA- 1.2, TRMM NN- 1.0, TRMM SG- 1.0, TRMM WA- 1.0
- Choctawhatchee(c) Evaluation: MERRA NN- 1.4, MERRA SG- 1.1, MERRA WA- 1.4, TRMM NN- 1.2, TRMM SG- 0.8, TRMM WA- 1.1;
- Clio Evaluation: MERRA NN- 0.9, MERRA SG- 0.9, MERRA WA- 0.9, TRMM NN- 1.2, TRMM SG- 1.1, TRMM WA- 1.0

All six watersheds contained about the same amount of forested land cover (38-50 percent), with the Neuse having the highest percent urbanization (17 percent). Though land cover affects the hydrology of a watershed, the models are likely too coarse in spatial resolution to attribute differences in simulation to observations.

Drainage basin size is a major factor in hydrologic modeling. As the basin size increases, it is more likely that ground-based stations will not be able to capture all the meteorologic

variability. Global or near-global products are not affected by this and offer a consistent sampling area for each grid over an entire watershed. As watershed area increased, TRMM produced better simulations and for the largest basin actually exceeded performance of the ground based product.

The Choctawhatchee watersheds were all completely contained within the Coastal Plains region and varied only slightly in land cover. This allows for the opportunity to examine differences in scale without the effects of the other major variables. Watersheds can be analyzed based on differences in scale alone. It is clear that the RSE drops (or doesn't change) for every scenario as the scale of the watershed increases. This is a strong indication that larger watersheds will have a greater benefit from remotely-sensed precipitation products.

- Choctawhatchee(a) (2,315 km²) (Calibration: MERRA NN- 2.0, MERRA SG- 2.6, MERRA WA- 2.2, TRMM NN- 1.2, TRMM SG- 1.3, TRMM WA- 1.1);
- Choctawhatchee(c) (9,125 km²) (Calibration: MERRA NN- 1.1, MERRA SG- 1.9, MERRA WA- 1.5, TRMM NN- 0.8, TRMM SG- 1.1, TRMM WA- 0.9);
- Choctawhatchee(b) (11,406 km²) (Calibration: MERRA NN- 0.9, MERRA SG- 1.1, MERRA WA- 1.1, TRMM NN- 0.8, TRMM SG- 0.8, TRMM WA- 0.9);
- Choctawhatchee(a) Evaluation: MERRA NN- 2.2, MERRA SG- 2.7, MERRA WA- 2.5, TRMM NN- 1.2, TRMM SG- 1.6, TRMM WA- 1.6);
- Choctawhatchee(c) Evaluation: MERRA NN- 1.4, MERRA SG- 1.1, MERRA WA- 1.4, TRMM NN- 1.2, TRMM SG- 0.8, TRMM WA- 1.1);
- Choctawhatchee(b) Evaluation: MERRA NN- 1.0, MERRA SG- 1.0, MERRA WA- 1.0, TRMM NN- 1.0, TRMM SG- 0.8, TRMM WA- 0.8)

Seasonal Fits

Seasonal flows are related to streamflow magnitude. In the study region the highest flows are during the Spring and low flows are typically associated with the Fall. TRMM and MERRA products had difficulty producing simulations that could be both high and low extremes.

5.3 Cross Calibration

To assess the quality of the calibration period as a representative time period of the watershed, a cross calibration was performed. This was done by calibrating the model over the evaluation period (latter portion of the dataset) and then using these parameter sets on the calibration period. If the standard residual errors of both sets are similar, it can be said that the original calibration period contained adequate information to use as a predictor for the evaluation period.

Cross calibration was performed on the nearest neighbor scenarios for the Choctawhatchee(a) and Choctawhatchee(b) watersheds. Tables 5.2 and 5.3 show the standard residual errors for both calibration and cross calibration for the four scenarios mentioned above.

Standard residual errors were closer in value for the Choctawhatchee(b) watershed scenarios with the TRMM (NN) scenario during the evaluation period having the worst ratio (16.1 percent). Choctawhatchee(a) scenarios were much further apart, with only the TRMM (NN) scenario during the calibration period ratio falling under 10 percent (8.6).

The wide margin in ratios between TRMM and MERRA driven scenarios for the same watersheds suggest that there may be something other than watershed behavior effecting these values. Errors in input data or model structure could be contaminating the model calibration process.

5.4 Data Reduction

A correlation matrix and PCA analysis were performed on the datasets. High correlations were found between metrics NSE, R^2 , and mNSE and for MAE and RMSE, suggesting that there may be some redundancy within these two groups. From the PCA, it becomes apparent that these metrics do well explaining 96 percent of the variation between observed and simulated streamflow. The PCA also shows that there is not a single metric within the two correlated groups that is more dominant than others in explaining the variation.

PCAs between watershed model and metrics, simulation type and metrics, period and metrics, input product and metrics, and input method and metrics do not show a clear explanation of variation between observed and simulated streamflow.

PCAs between scale variable and metrics account for some of the explanation of variation in the second factor, but it is not clear why this occurs.

5.5 Caveats

Differences in streamflow predictions between scenarios have been attributed to atmospheric input sources and method of input. Other important sources of uncertainty can effect predictions and subsequent analysis.

Uncertainty Associated with Observed Streamflow Gage Data

Observed data is commonly treated as theoretical values during calibration and statistical analysis during the modeling process. There are, of course, measurement and interpolation/extraction uncertainties associated with observed data. Also, for the standard residual error analysis ground-based scenarios are treated as the true value, which is often not the case.

Uncertainty within Calibrated Parameters

Even when a model has been “calibrated” there are still upper and lower uncertainty bounds associated with each calibrated parameter. Because the relationship between parameters is highly nonlinear, adjustments to any one parameter in the set can significantly affect the overall objective function. It is assumed that the PEST calibration performed on each of the scenarios is the best objective function that can be achieved while staying within the parameters individual limits.

Uncertainty in the Model Structure

The inability of hydrological models to perfectly replicate the physical processes involved in rainfall-runoff transformation is a major source of uncertainty. It is also a very difficult source to overcome. This thesis did not fully explore the suite of numerical analysis techniques to reduce this uncertainty.

Table 5.1: Comparison of input methods: This table lists the best input product for the particular watershed, scale, and time period. The best product is based on combined values of the BASSET statistics.

Watershed	Calibration Period		Evaluation Period	
	Linear	Logarithmic	Linear	Logarithmic
Choctawhatchee(a)	Ground	Ground	Ground	Ground
Choctawhatchee(b)	TRMM/Ground	TRMM	Ground	Ground
Choctawhatchee(c)	TRMM/Ground	Ground	TRMM/Ground	Ground
Clyo	Ground	Ground	Ground	Ground
Neuse	Ground	Ground	Ground	Ground
Ogeechee	Ground	Ground	Ground	N/A

Table 5.2: Cross Calibration: standard residual errors for the Choctawhatchee(a) and Choctawhatchee(b) during the calibration period.

Metric	Calibration Period			
	Choct(a)	Choct(a) sw	Choct(b)	Choct(b) sw
beta_m (NN)	2.0	1.7	0.9	0.9
beta_t (NN)	1.2	1.3	0.8	0.7

Table 5.3: Cross Calibration: standard residual errors for the Choctawhatchee(a) and Choctawhatchee(b) during the evaluation period.

Metric	Evaluation Period			
	Choct(a)	Choct(a) sw	Choct(b)	Choct(b) sw
beta_m (NN)	2.2	1.6	1.0	1.1
beta_t (NN)	1.2	1.0	1.0	0.9

Chapter 6

Summary and Conclusions

The objective of this study is to assess the feasibility of supplementing or replacing ground-based meteorological data with remotely sensed data as inputs to hydrologic models. In general, model performance is evaluated for different scenarios by comparing the calibrated model to observed streamflow data over a range of discharges. The types of scenarios examined include the type of input precipitation datasets (e.g. ground-based, TRMM MPA, MERRA) as well as the data input method (e.g. by watershed segment, areally weighted average, and nearest neighboring grid cell). Statistics were computed for each scenario using BASSET, and statistical measures were estimated for the entire data series, stormflow data only, and baseflow data only on both untransformed and log-transformed discharges. These assessments were performed for a calibration period as well as an evaluation period so that predictive ability could be assessed.

Hydrologic Simulation Program-FORTRAN (HSPF) is a spatially distributed streamflow simulation model that is used to model six watersheds varying in size from 2,315 to 11,400 km². Observed streamflow is compared with simulations that use different combinations of input precipitation (e.g. ground based, TRMM MPA, MERRA), as well as input method (e.g. by watershed segment, areally weighted average, or nearest neighboring grid cell).

TRMM precipitation and MERRA potential evapotranspiration data provide acceptable results to ground-based meteorological data. As basin size increases, TRMM/MERRA coupled inputs performed better and actually exceeded ground based inputs for the largest watershed modeled. This is likely due to the sparseness and inconsistent placement of ground-based meteorological data over large scales.

It is recommended based on this study that TRMM/MERRA coupled precipitation and potential evapotranspiration inputs would be a valid driver of HSPF streamflow models in replacement of or in absence of ground-based meteorological data. Evaluation of modeled simulations should be tailored to the needs of the user. Analyzing outputs by separating high and low flows can aid in determining the best fit given different scenarios.

Chapter 7

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Appendix A

Model Input Data Files

The tables presented below catalog the ground stations and TRMM and MERRA grids used in each model scenario. Each time series has a corresponding Data Set # (DSN) which gives it a unique identity.

Table A.1: Data Set Numbers (DSN) for observed streamflow and pour point data

DSN	Clyo	Neuse	Ogeechee	Choc (a)	Choc (b)	Choc (c)
Observed Flow	12	113	2111	1114	4/4333	4444
Pour Point Flow	9999	N/A	N/A	N/A	N/A	N/A

Table A.2: Data Set Numbers (DSN) of the ground-based meteorological stations used for the Clyo watershed

Station Name	PEVT DSN	PREC DSN	Station #	Area (mi ²)	Proportion
Warrenton	46	41	GA099141	348.64	0.09
Johnston 4 SW	36	31	SC384607	868.99	0.23
Augusta Bush Field AP	16	11	GA090495	1084.19	0.29
Allendale 2 NW	6	1	SC380126	864.93	0.23
Waynesboro 2 S	56	51	GA099194	576.77	0.15
WA DSN (PEVT)	99		Total:	3,743.53	
WA DSN (PREC)	98				

Table A.3: Data Set Numbers (DSN) of the MERRA meteorological grids used for the Clyo watershed

	PEVT DSN	PREC DSN	Station #	Area (mi ²)	Proportion
	6556	6558	M146247	285.78	0.08
	6446	6448	M147246	665.80	0.18
	5012	6228	M147247	1199.59	0.32
	5011	6118	M147248	570.93	0.15
	5008	5009	M148245	210.69	0.06
	5010	6338	M148246	627.38	0.17
	6666	6668	M148247	183.34	0.05
WA DSN (PEVT)	5698		Total:	3,743.53	
WA DSN (PREC)	5699				

Table A.4: Data Set Numbers (DSN) of the TRMM meteorological grids used for the Clio watershed

MERRA Grid	MERRA DSN	301 DSN	Station #	Area (mi ²)	Proportion
M146247	6556	5014	T03900333	392.64	0.10
		5013	T03910332	173.62	0.05
		6991	T03910333	251.57	0.07
		6223	T03910334	271.65	0.07
		6111	T03910335	266.97	0.07
		6771	T03910336	134.38	0.04
M147246	6446	6881	T03920332	282.66	0.08
		6113	T03920333	251.39	0.07
		6443	T03920334	245.22	0.07
		6551	T03920335	169.56	0.05
M148246	5010	5015	T03930331	291.99	0.08
M148246	5010	6441	T03930332	347.19	0.09
M148247	6666	6331	T03930333	276.21	0.07
		5002	T03940330	192.81	0.05
		5003	T03940331	195.69	0.05
WA DSN	5697	Total:		3,743.53	

Table A.5: Data Set Numbers (DSN) of the ground-based meteorological stations used for the Neuse watershed

Station Name	Old DSN	Station #	Area (mi ²)	Proportion
Smithfield	161/166	NC317994	721.7	0.31
Clayton WTP	171/176	NC311820	417.8	0.18
Raleigh State Univ	141/146	NC317079	565.4	0.24
Durham	121/126	NC312515	432.3	0.18
Roxboro 7 ESE	151/156	NC317516	212	0.09
WA DSN (PEVT)	4889	Total:	2,349.2	
WA DSN (PREC)	4999			

Table A.6: Data Set Numbers (DSN) of the MERRA meteorological grids used for the Neuse watershed

	PEVT DSN	PREC DSN	Station #	Area (mi ²)	Proportion
	7116	7118	M151252	207.95	0.09
	7336	7338	M152252	960.60	0.41
	7226	7228	M152251	656.52	0.28
	7446	7448	M153251	524.09	0.22
WA DSN (PEVT)	7889		Total:	2,349.16	
WA DSN (PREC)	7999				

Table A.7: Data Set Numbers (DSN) of the TRMM meteorological grids used for the Neuse watershed

Base DSN	Neuse DSN	Station #	Area (mi ²)	Proportion
6111	7111	T04060342	334.23	0.14
6331	7331	T04050343	327.47	0.14
6221	7221	T04050342	313.31	0.13
6551	7551	T04060343	163.46	0.07
6441	7441	T04060341	526.69	0.22
6661	7661	T04050344	148.46	0.06
6881	7881	T04040344	327.62	0.14
6771	7771	T04030344	207.91	0.09
WA DSN	7779	Total:	2,349.16	

Table A.8: Data Set Numbers (DSN) of the ground-based meteorological stations used for the Ogeechee watershed

Station Name	Old DSN	Station #	Area (mi ²)	Proportion
Midville Exp Sta	1888/1889	GA095863	135.5	0.10
Louisville 1 E	1777/1778	GA095314	432.4	0.33
Sandersville	1666/1667	GA097777	247.6	0.19
Warrenton	1333/1334	GA099141	382.7	0.29
Siloam 3 N	1999/1990	GA098064	122.2	0.09
WA DSN (PEVT)	902	Total:	1,320.4	
WA DSN (PREC)	901			

Table A.9: Data Set Numbers (DSN) of the MERRA meteorological grids used for the Ogeechee watershed

	PEVT DSN	PREC DSN	Station #	Area (mi ²)	Proportion
	2167	2168	M146246	901.9	0.68
	5116	5117	M146247	418.5	0.32
WA DSN	3667		Total:	1,320.4	
	5667				

Table A.10: Data Set Numbers (DSN) of the TRMM meteorological grids used for the Ogeechee watershed

	Base DSN	Ogeechee_DSN	Station #	Area (mi ²)	Proportion
	2777		T03900332	174.8	0.13
	5444		T03880333	231.4	0.18
	2333		T03890333	140.4	0.11
	5222		T03890332	249.7	0.19
	5333		T03890331	133.4	0.10
	5111		T03900331	255.3	0.19
	5555		T03880332	88.9	0.07
	2999		T03870334	46.5	0.04
WA DSN	3666		Total:	1,320.4	
	5666				

Table A.11: Data Set Numbers (DSN) of the ground-based meteorological stations used for the Choctawhatchee (b) watershed

Station Name	Old DSN	Station #	Area (mi ²)	Proportion
Geneva No 2	61/66	AL013251	1616.5	0.37
Headland	41/46	AL013761	1731.5	0.39
Chipley	1/6	FL081544	525.5	0.12
De Funiak Springs	21/26	FL082220	530.4	0.12
WA DSN (PEVT)	96	Total:	4,403.9	
WA DSN (PREC)	97			

Table A.12: Data Set Numbers (DSN) of the MERRA meteorological grids used for the Choctawhatchee (b) watershed

	PEVT DSN	PREC DSN	Station #	Area (mi ²)	Proportion
	5226	5227	M141242	1552.8	0.35
	4001	5887	M141243	1107.7	0.25
	4002	4000	M142242	583.9	0.13
	5146	5147	M142243	713.5	0.16
	5116	5157	M142244	446.0	0.10
WA DSN (PEVT)	4998	Total:	4,403.9		
WA DSN (PREC)	4999				

Table A.13: Data Set Numbers (DSN) of the TRMM meteorological grids used for the Choctawhatchee (b) watershed

MERRA	DSN	Station #	Area (mi ²)	Proportion
5226	9611	T03750324	376.87	0.09
	9631	T03750325	243.47	0.06
5226	4007	T03760322	332.57	0.08
5226	4006	T03760323	357.83	0.08
	4005	T03760324	256.35	0.06
	5222	T03760325	255.67	0.06
4001	9621	T03760326	391.37	0.09
	4008	T03770322	192.70	0.04
	4004	T03770323	327.22	0.07
	4003	T03770324	277.99	0.06
	5444	T03770325	255.54	0.06
	5666	T03770326	254.86	0.06
5116	9601	T03770327	387.31	0.09
	5777	T03780325	164.79	0.04
	5555	T03780326	223.95	0.05
5116	5111	T03780327	105.42	0.02
WA DSN	4996	Total:	4,403.90	

Table A.14: Data Set Numbers (DSN) of the ground-based meteorological stations used for the Choctawhatchee (c) watershed

Station Name	Old DSN	Station #	Area (mi ²)	Proportion
Geneva No 2	61/66	AL013251	1791	0.51
Headland	41/46	AL013761	1732	0.49
WA DSN (PEVT)	98	Total:	3,523	
WA DSN (PREC)	99			

Table A.15: Data Set Numbers (DSN) of the MERRA meteorological grids used for the Choctawhatchee (c) watershed

	PEVT DSN	PREC DSN	Station #	Area (mi ²)	Proportion
	4001	5887	M141243	1107.7	0.31
	5146	5147	M142243	713.5	0.20
	5116	5157	M142244	446.0	0.13
	5226	5227	M141242	1017.3	0.29
	4002	4000	M142242	238.6	0.07
WA DSN (PEVT)	4998	Total:	3,523.1		
WA DSN (PREC)	4999				

Table A.16: Data Set Numbers (DSN) of the TRMM meteorological grids used for the Choctawhatchee (c) watershed

MERRA	Base DSN	ChoctFull2 DSN	Station #	Area (mi ²)	Proportion
5226		9611	T03750324	377	0.11
		9631	T03750325	243	0.07
		4006	T03760323	239	0.07
5226		4005	T03760324	256	0.07
		5222	T03760325	256	0.07
4001		9621	T03760326	391	0.11
		4004	T03770323	107	0.03
4002		4003	T03770324	261	0.07
		5444	T03770325	256	0.07
		5666	T03770326	255	0.07
5116		9601	T03770327	387	0.11
		5777	T03780325	165	0.05
		5555	T03780326	224	0.06
		5111	T03780327	105	0.03
WA DSN	4997		Total:	3,523	

Table A.17: Data Set Numbers (DSN) of the ground-based meteorological stations used for the Choctawhatchee (a) watershed

Station Name	Old DSN	Station #	Area (mi ²)	Proportion
Headland	1131/1136	AL013761	563.1	0.63
Clayton	2111/1116	AL011725	331.1	0.37
WA DSN (PEVT)	904	Total:	894.2	
WA DSN (PREC)	903			

Table A.18: Data Set Numbers (DSN) of the MERRA meteorological grids used for the Choctawhatchee (a) watershed

	PEVT DSN	PREC DSN	Station #	Area (mi ²)	Proportion
	6136	6447	M142243	598.6	0.85
	6116	6557	M142244	105.6	0.15
WA DSN (PEVT)	6889	Total:	704.2		
WA DSN (PREC)	6779				

Table A.19: Data Set Numbers (DSN) of the TRMM meteorological grids used for the Choctawhatchee (a) watershed

	DSN	Station #	Area (mi ²)	Proportion
	6777	T03780325	123.3	0.18
	6555	T03780326	227.4	0.32
	6131	T03770326	171.1	0.24
		T03770325	84.1	0.12
	6111	T03780327	98.4	0.14
WA DSN	6999	Total:	704.2	

Appendix B

Model Output Data Files

Model output files are located under their respective model folders in the directory:

- `..\modelout.xlsx`

Files found in these folders contain simulated streamflow along with observed streamflow data for both calibration and evaluation periods.