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Stream Temperature Modeling: A Modeling Comparison for Resource Managers and Climate Change Analysis

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Stream Temperature Modeling:

A Modeling Comparison for Resource Managers and Climate Change Analysis

A MS Project Presented

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Abstract

In the Northeast U.S. increasing stream temperatures due to climate change pose a serious threat to cool and cold water fish communities, as well as aquatic ecosystems as a whole. In this study, three stream temperature models were implemented for two different case-study basins in the Northeast Climate Science Center region. Two coupled hydrology-stream temperature (physical) models were used: VIC-RBM and SWAT-Ficklin et al. (2012). The third model implemented was a nonlinear regression (statistical) model developed by Mohseni et al. (1998). Metrics were developed to assess these models regarding their prediction skill, data input requirements, spatial and temporal resolutions, and "user-friendliness." This comprehensive assessment will be employed by aquatic resource managers in need of projected stream temperatures for management decisions in the face of climate change. Additionally, these models were used to predict stream temperatures under a range of future air temperature and precipitation scenarios for the study basins. These basins were the Westfield Basin (1,338 km2) in western Massachusetts and the Milwaukee Basin (2,220 km2) in Wisconsin. The climate change analysis was performed using a range of potential precipitation changes and air temperature increases (similar to a climate stress test). Precipitation scenarios ranged from 90% of observed to 130% of observed (in increments of 10%) and daily air temperature increases ranged from 0° C to 7° C (in increments of 1° C); the combinations of 5 precipitation scenarios and 8 air temperature scenarios yielded 40 different climate scenarios that were evaluated by each model. The impacts of climate change on these temperature and precipitation ranges was determined for the two watersheds and during specific seasons of the year.

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1. Introduction

"Freshwater habitats are the most endangered worldwide."

Peter Moyle, Distinguished Professor, University of California Davis

1.1 Problem Statement and Objective

Freshwater fish species have suffered significantly from anthropogenic influences on their habitat including, but not limited to: chemical pollution, dams and other infrastructure, land-use changes, and thermal degradation (Caissie 2006; Coutant 1999; Hester and Doyle 2011; Poole and Berman 2001; Revenga and Kura 2003). Fish habitats will continue to be impacted by the most dramatic and concerning phenomena of our time – climate change. Natural resource management is challenging due to the natural variability of our climate, our lack of understanding of species and population dynamics, and our inability to forecast with precision the impact of management action on complex biological systems (Cilliers et al. 2013). Natural systems typically have a large number of dynamic and interrelated components. Many of these impacts are experienced directly, while others create nonlinear feedback loops. Also, natural systems vary temporally and are affected by prior system states (Cilliers 1998; Cilliers et al. 2013). Quantifying the impacts of projected climate change on such complicated systems is challenging.

When considering the incorporation of climate change projections into aquatic resource management plans, decision makers must consider not only the broad global forecasts that are readily available but also forecasts that are representative of local changes. To do so, managers must select from a number of diverse models that are available to ensure the effectiveness of their potential actions.

Climate change is causing significant alarm among aquatic resource managers, because it alters the hydrologic cycle, stream characteristics and extreme temperatures. For example, Hodgkins and Dudley (2006) analyzed 80 stream gage stations in North America north of 41° north latitude, finding 64% have significantly earlier winter-spring streamflows over an 80 year period. This result is corroborated by Campbell et al. (2011), who observed at Hubbard Brook Experimental Forest in New Hampshire from 1965-2008 that peak discharge due to snowmelt is occurring earlier and at reduced magnitudes due to earlier snowmelt and reduced snowpack. Isaak et al. (2010) observed that from 1993-2006 basin annual mean stream temperature increased by 0.38° C and maximums increased by 0.48° C for a river network in central Idaho. In the Columbia River Basin average summer stream temperatures are projected to increase 5.2° C by the 2080s under RCP 8.5 emissions scenario (Ficklin et al., 2014). These changes in flow regimes and stream temperatures will influence the aquatic species that can be sustained in various rivers and streams and their potential management.

Stream temperature is strongly correlated with local air temperature (Mohseni et al. 1998; Caissie et al. 2001; Morrill et al. 2005; Ficklin et al. 2012; Yearsly 2012), suggesting that projected increases in air temperature will result in increases in stream temperatures in the future (Peterson and Kitchell 2001; Morrison et al. 2002). For aquatic resource managers, changing stream temperatures are of great concern. Managers are constrained by limited historical data for many streams and an incomplete understanding of the extent to which changes in air temperature and precipitation will impact streamflow and water temperature. Computer models containing forecasts of future air temperatures and precipitation can offer insight into predicted changes in flow regimes and stream temperatures.

In recent years a myriad of stream temperature models have become available, with a wide range of required model inputs and with different spatial and temporal resolutions. Each model has unique strengths and weaknesses. The selection of one or more suitable stream temperature models depends significantly on the intended use and management actions for simulated stream temperatures. For this work, three widely used stream temperature models that have potential value to resource managers were implemented in two different basins in the Northeast Climate Science Center region with the goal of providing guidance to aquatic resource managers in stream temperature model selection (including for climate change analyses). This was done to promote efficiency and effectiveness in resource management. When able to quickly select the model that best meets their needs, managers will be better equipped for decision-making and subsequently management actions. The chapters of this thesis are organized as follows: Chapter 2 provides background on climate change and natural resource management, the impacts of stream temperature on aquatic ecosystems, a history and description of water quality models, details the specific study basins, describes the Structured Decision Making (SDM) method, and outlines the metrics to be used for assessment. Chapter 3 presents the research methodology of implementing and assessing the models, as well as a description of the climate change analysis. The results of the model comparison and climate change analysis are presented in Chapter 4 and the conclusions and future work are presented in Chapter 5.

2. Background

An important goal of natural resource management is to conserve or create a healthy ecosystem. In this research a healthy ecosystem is defined as one that is able to maintain its structure and function over time when it encounters external stress (Costanza and Mageau 1999). Anthropogenic alterations to the natural environment have imposed significant stresses on the health of various ecosystems. Climate change, in particular, poses extreme threats to ecosystem health, to an extent that is not easily quantified due to the complexity of both the systems and the stressor. The major concerns in natural resource management regarding climate change include the following general categories: fitness, habitat, phenology, and survival.

2.1 Stream Temperature and Aquatic Ecosystems

Stream temperature is a critical component of aquatic ecosystem health. It affects the chemical processes occurring in streams, and more directly for aquatic biota it impacts abundance, distribution, vitality, growth, survival, and phenological indices. Freshwater fish species are of particular interest to natural resource managers because of their importance in the ecosystem and their diminished populations as a result of anthropogenic alterations – historical and contemporary – to river corridors (including water quality degradation). As a result of this elevated level of interest and concern, species-specific thermal ranges for life-cycle stages have been relatively well-studied and documented for many fish, including "adult migration, spawning, egg incubation, embryo development, juvenile rearing, smoltification, and juvenile migration" (Coutant 1999). Hester and Doyle (2011) found that aquatic species are more sensitive to temperatures higher than their thermal optima than they are to temperatures lower than the optima. They also observed that fish are more sensitive to water temperature changes than invertebrates. Cold water fish species are of particular concern in the Northeast due to observed and projected stream temperature increases as a result of climate change. Eaton et al. (1995) used field surveys to determine maximum temperature tolerances for various species presented in Table 1.

Table 1: Tolerable maximum weekly average temperature for select species

Species	**Deg. C**
chum salmon	19.8
pink salmon	21.0
brook trout	22.4
mountain whitefish	23.1
cutthroat trout	23.3
coho salmon	23.4
chinook salmon	24.0
rainbow trout	24.0
brown trout	24.1
walleye	29.0
smallmouth bass	29.5

Many studies examined the impact of stream temperature on abundance. Ebersole et al. (2001) observed an inverse correlation between mean ambient maximum stream temperature and abundance of rainbow trout. Using downscaled GCM output, Morrison et al. (2002) predicted a 1.9° C increase in water temperature for the years 2070-2099 versus the historical period (1961-1990) in the Fraser River. This increase in temperature would significantly reduce spawning success and increase by a factor of 10 the exposure of salmon to water temperatures greater than 20° C. Morrison et al. (2002) determined this by comparing the current rates of salmon exposure to “excessively warm” stream temperatures with projected exposure rates. The number of 10-km reaches and hours where stream temperature exceeds 20° C were summed to determine cumulative exposure in degree reach hours (DRH).

Changes in aquatic species distribution due to thermal changes in stream can be explained by the “River Continuum Concept” (Vannote et al. 1980). This approach describes relationships between physical characteristics of river habitat and resident communities of aquatic biota. It suggests that both seasonal and daily variations of water temperatures are important determinates for aquatic species distribution, with anthropogenic changes in water temperature causing aquatic communities to along the stream corridor. Butryn et al. (2012) predicted brook trout distribution in the Dog River, Vermont using summer temperature metrics as predictor variables, with 92% correct classification of the observations. From 1993 to 2006 Isaak et al. (2010) estimated that bull trout in central Idaho lost 11-20% of their cold water spawning and early juvenile rearing habitat as a result of an annual mean stream temperature increase of 0.38° C (maxima increased by 0.48° C). These temperature increases only minimally affected the thermally-suitable habitat of rainbow trout, with small shifts toward higher elevations as reaches that had previously been too cold warmed. Mohseni et al. (2003) studied 764 stream gaging stations in the contiguous U.S. to project the potential habitat changes of 57 fish species under climate change. Using GCM projections and a stream temperature model, (Mohseni et al. 1998) they predicted a 36% decrease in the number of stations with habitat suitable for cold water fishes and a 15% decrease for cool water fishes; whereas, thermally suitable habitat for warm water fishes was projected to increase by 31%.

Vitality of fish species is also affected by climate change. Eliason et al. (2011) studied cardiorespiratory physiology in adult sockeye salmon, finding that aerobic performance required more energy in warmer water. Expending greater amounts of energy to survive reduces overall fish vitality. In the case of the sockeye, a reduction in fitness has been documented as climate change-induced increases in stream temperatures during summer migration has led to elevated mortality during spawning migration, meaning fewer fish are able to reproduce. Using a bioenergetics model driven by data from 1933 to 1996 in the Columbia River, Peterson and Kitchell (2001) predicted predation rates on juvenile Pacific salmonids by northern squawfish to be 68-96% higher for the warmest (water temperature) year compared to the coldest year.

Researchers developing growth models for various fish species have developed species-specific growth-rates based on stream temperature. Examples include brown trout predictive growth models (Elliott 1975a, b; Elliot and Hurley 1995; Elliott et al. 1995; Jensen 1990), and an Atlantic salmon growth model (Elliott and Hurley 1997). Although specific optimum temperature ranges differ between fish species, growth rates according to temperature can be generalized as follows: growth rates increase as temperature rises (below the optimum thermal range), growth rates plateau over the thermal optimum range, growth rates decline rapidly above the optimum temperature range, loss of body mass occurs slightly below lethal temperatures (Coutant 1999).

Lethal water temperatures resulting from climate change are of great concern for cold water fish species in the Northeast. In the well-documented thermal ranges for different fish species and their respective range of life-stages, ultimate (survivable for ten minutes) and incipient (survivable for up to one week) lethal water temperatures have been documented. For fish in temperate latitudes, 0° C is typically the lower bound of survivable temperatures with upper bounds varying significantly between species (Coutant 1999). Table 2 presents the lower and upper incipient and ultimate temperature ranges for three different fish species at three different life-cycle stages (Elliott and Elliot 2010).

Table 2: Critical temperatures (deg. C) for survival at different life stages of Atlantic salmon, brown trout, and Arctic charr as presented by Elliott & Elliott (2010)

	Salmo salar		*Salmo trutta*		*Salvelinus alpinus*	
	Lower	Upper	Lower	Upper	Lower	Upper
Eggs	0	16	0	13	0	8
Alevins						
Incipient	0–2	23–24	0–1	20–22	0–0·3	19–21
Ultimate	0–1	24–25	0	22–24	0–0·2	23–27
Parr + smolt						
Incipient	0–2	22–28	0–0·7	22–25	0–1	22–23
Ultimate	−0.8	30–33	−0·8	26–30	−1.0	26–27
Feeding	0–7	22–28	0·4–4	19–26	0·2	21–22

Phenology is the relationship between climate and periodic biological phenomena. Temperature initiates many life events for flora and fauna. Water temperature is a very important phenological indicator for aquatic species, including fish. Juanes et al. (2004) examined 23 years of data on the migration timing of Atlantic salmon from two locations in the Connecticut River watershed. They found that both the dates of first capture and median capture dates have shifted earlier by approximately 0.5 days/year in correlation with long-term changes in temperature. These results were corroborated by observed shifts to earlier peak migration times in Maine and Canada (Juanes et al. 2004). In a spawning phenology study conducted by Warren et al. (2012), a correlation was observed between elevated summer temperatures and a delay in spawning for brook trout (*Salvelinus fontinalis*) in a mountain lake. An increase of 1° C in the summer mean of maximum daily air temperatures delayed spawning by approximately 1 week (Warren et al. 2012).

The effects of stream temperature on fish species extends to the ecosystem level, including prey abundance. In benthic insect communities of small and medium-sized streams, Haidekker and Hering (2008) observed quantitative differences in community composition correlated with water temperature parameters. Daufresne and Boet (2007) performed a meta-analysis assessing the effect of climate change on stream organisms. They observed "important changes in total abundance, structures and diversity of fish communities, significantly linked to the temperature during reproduction." Broad awareness of anthropogenic thermal degradation of rivers and streams began in the environmental movement of the 1970s.

2.2 Water Quality Modeling

2.2.1 History

Early "sanitary engineers" were very interested in water quality for several reasons, including the transmission of disease through water ways and the development of anaerobic conditions in rivers due to the discharge of human wastes. Streeter and Phelps (1925) developed the first widely used water quality modeling concepts, long before the availability of computers. These early approaches to water quality modeling were well establish by the early 1970, when the availability of computing increased and the need to estimate the impacts of wastes on receiving water increased dramatically due to the passage of the Clean Water Act (CWA, or PL 92-500) in 1972. This federal law established the Environmental Protection Agency's (EPA's) regulatory authority over point-source pollution through the National Pollutant Discharge Elimination System (NPDES). Section 316 of the CWA specifically addresses thermal discharges as a form of water pollution. Water quality models branched in three separate but related directions – dissolved oxygen modeling due to the discharge of wastes, nutrients/algae/toxins modeling that tracked oxygen demand and the transport of toxics discharges, and temperature modeling, which focused on steam temperature and its impacts on other rate coefficients. Shanahan (1985) summarized the applications of early water temperature modeling: "Computations of water temperature are employed to determine the environmental impacts of thermal discharges, to evaluate the performance of cooling ponds used to dispose of waste heat from power plants, or to evaluate the hydrothermal characteristics of water bodies in general. They are an essential part of the design of waste heat disposal structures and systems, and in the assessment of environmental effects of waste heat disposal." Perhaps the most well-known and widely used of the earliest water quality models was QUAL-II, developed for the EPA. In its early form, QUAL-II could simulate up to thirteen water quality constituents, including: dissolved oxygen, biochemical oxygen demand, temperature, algae as chlorophyll a, ammonia as N, nitrite as N, nitrate as N, dissolved orthophosphate as P, and coliforms in dendritic, well-mixed streams in one-dimension along the main direction of flow (Roesner et al. 1981).

Due to significant advances in computing capabilities, a multitude of stream temperature models have been developed. These models fall into two major categories: physically-based and statistical. Physical models are built on mathematical equations governing physical processes. They employ energy budgets and/or water balance equations to calculate stream temperatures. Statistical models rely heavily on air temperature data inputs to predict stream temperatures, coupling them by statistical relationships. These models are described in detail below, noting strengths and weaknesses.

2.2.2 Physical Models

Physical stream temperature models typically perform energy balances of heat fluxes in river environments and mass balances of water in river systems. Physical models simulate stream temperature in one or more dimensions, with the simplest models estimating temperatures along the principle axis of stream flow. One-dimensional models are used in rivers and streams that are well-mixed. In more complex environments (such as lakes and estuaries) models with higher dimensions may be necessary to estimate temperatures that vary spatially. In river environments, heat exchange occurs at the air-water interface and streambed-water interface; managed/impacted rivers also experience heat exchange through thermal effluent and water extractions. At the air-water interface, heat flux occurs via solar radiation, net long-wave radiation, evaporation, and convective heat transfer. Heat flux at the streambed-water interface occurs through geothermal heat conduction and advection from groundwater and hyporheic flows (Caissie 2006).

Water quality temperature models that are physically based can require significant data input (e.g. meteorological data, stream geometry, land use, and hydrology), but provide an opportunity to evaluate changes in temperature through broad scenario evaluation. Modeled scenarios can include changes in land use, altered hydrologic regimes, introduction of water impoundment structures, and projected climate change.

A recently developed physical stream temperature (Yearsley 2009) uses a semi-Lagrangian approach to solve the time-dependent equations of the one-dimensional thermal energy budget. The River Basin Model (RBM) utilizes existing extensive gridded data sets (for model-forcing functions) for the assessment of water temperature. Yearsley (2012) later coupled a macroscale hydrologic model (Variable Infiltration Capacity, or VIC) with RBM. VIC, developed by Liang et al. (1994) is a physically-based model that balances water and/or surface energy budgets on a per grid cell basis. Inputs required include meteorological forcing files, soil parameters, vegetation parameters, and snowband information. VIC (and associated routing algorithms) output disaggregated meteorological forcings and gridded channel flows, which are then input to RBM to estimate hydraulic properties, stream speed, and thermal energy fluxes at the air-water interface (per grid cell). Initial conditions for RBM are obtained from the Mohseni et al. (1998) nonlinear stream temperature regression model. Like the regression model, stream temperatures are predicted on a weekly time-step. Van Vliet et al. (2012) developed a framework to refine the temporal resolution of the coupled VIC-RBM model to simulate daily river discharge and temperatures. This was done by utilizing the Mohseni et al. (1998) nonlinear regression modified by van Vliet et al. (2011) to output stream temperatures on a daily time-step to determine initial conditions. Figure 1 presents the inputs and outputs for VIC-RBM, as well as the full suite of model components.

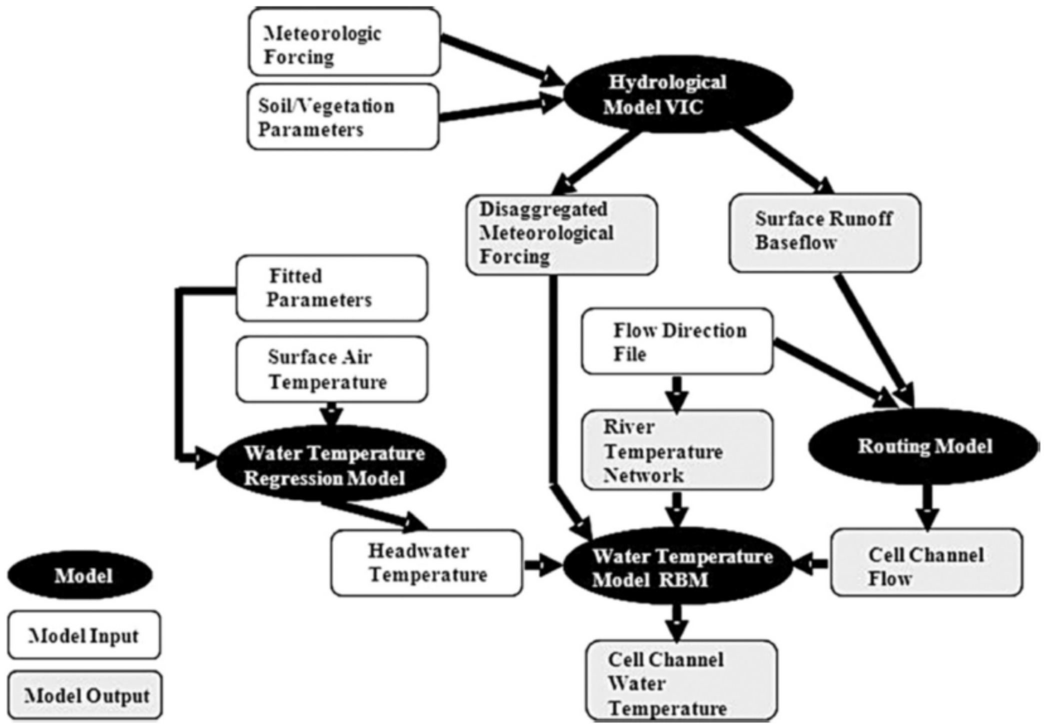

Figure 1: Flow Diagram for VIC-RBM (Fig. 2 from Yearsley 2012)

A second example of a commonly used hydrology model coupled with a new stream temperature model is the Soil and Water Assessment Tool (SWAT) paired with a stream temperature model developed by Ficklin et al. (2012). Developed to evaluate the impacts of different management scenarios on water resources in river basins – particularly non-point source pollution – SWAT is a continuous-time, semi-distributed, process-based river basin model (Arnold et al. 1998). SWAT utilizes an internal statistical stream temperature component for modeling various in-stream biological and water quality processes. The internal stream temperature model employs a linear relationship between air temperature and water temperature developed by Stefan and Preud'homme (1993), which functions at minimum on a daily time-step. The stream temperature model developed by Ficklin et al. (2012) incorporates meteorological (air temperature) and hydrological conditions (streamflow, snowmelt, groundwater, surface runoff, and lateral soil flow) into stream temperature calculations while utilizing existing inputs to the SWAT model. Stream temperature is calculated through three components: temperature and amount of local water contribution within the subbasin; temperature and inflow volume from upstream subbasin(s); and heat transfer at the air-water interface during the streamflow travel time in the subbasin.

2.2.3 Statistical Models

Statistical water temperature models seek mathematical relationships to estimate potential changes in temperatures as functions of pre-specified variables. Statistical models require significantly less input data than physical models, making them more appealing for certain applications. Early statistical stream temperature models used a linear regression to correlate air temperatures with predicted stream temperatures (Smith 1981). However, linear regressions are often inappropriate for use in modeling stream temperatures year-round as linearity is an inappropriate approximation at the highest and lowest temperatures (due to increased evaporative cooling and freezing respectively) and it does not account for hysteresis. To address these issues, Mohseni et al. (1998) developed a four-parameter nonlinear regression model that is widely applied. The model employs an S-shaped function to better fit the relationship between air and stream temperature and applies separate functions for warming and cooling seasons. The four parameters of the nonlinear function are estimated minimum and maximum stream temperatures, slope of the function, and air temperature at the inflection point. Highly impacted streams may not fit the S-shaped function and the nonlinear regression cannot be applied. The Mohseni et al. (1998) nonlinear regression operates on a weekly time-step, which in some cases may not adequately represent a temporal resolution sufficiently detailed for resource managers.

In response to this need, van Vliet et al. (2011) increased the temporal resolution of the Mohseni et al. (1998) nonlinear regression to a daily time-step. This was accomplished by incorporating site-specific time-lags relating changes in air temperature to changes in water temperature and replacing daily maximum air temperature inputs with daily mean temperatures. Additionally, van Vliet et al. (2011) introduced a fifth parameter, a river discharge variable, into the existing nonlinear regression, which was particularly successful for stream temperature prediction during periods of heat waves and drought. Additional types of statistical models that have been applied to water temperature modeling include autoregressive models, periodic autoregressive models, artificial neural networks, and k-nearest neighbors (Benyahya et al. 2007).

2.2.4 Model Summary

Table 3 presents a summary of strengths and weaknesses of physical and statistical models.

Table 3: Summary of Model Type Strengths and Weaknesses

Model Type	Strengths	Weaknesses
Physical	• Can model different scenarios (e.g. landuse and climate) • Visual interfaces	• High data input requirements • Challenging to initiate/calibrate
Statistical	• Easy to initiate/calibrate • Low data requirements	• 0-dimensional • Can't model scenarios • Low temporal resolution

2.3 Study Basins

This research focuses on basins within the Northeastern U.S. (defined in this case, as New England and the Great Lakes states). The two basins selected for this study are representative of typical basins in the Northeast, allowing for region-wide trends in stream temperature due to climate change to be determined. These two basins are the Westfield River Basin in western Massachusetts and the Milwaukee River Basin located in southeastern Wisconsin. These basins have extensive stream temperature data available, U.S. Geological Survey (USGS) GAGES-II reference gages, relatively unimpaired flows, and natural resource management concerns.

2.3.1 Westfield Basin

The Westfield river basin is a sub-basin of the Connecticut River, originating in the Berkshire Mountains. It is approximately 1,344 km^2 and contains the longest uncontrolled river in the state of Massachusetts, the West Branch of the Westfield River. The Westfield basin hosts an excellent cold water fishery, supporting naturally reproducing or wild populations of brook trout and brown trout (Pioneer Valley Planning Commission 2006). There are eighty-two lakes, ponds, and impoundments in the basin, more than half of which (forty-eight) are larger than ten acres. The nearly 6,000 acres of open water in the Westfield river basin are utilized for recreation, wildlife habitat, industrial processing, waste assimilation, hydroelectric power, water storage, and drinking water supplies (Pioneer Valley Planning Commission 2006). There are five major water supply reservoirs in the basin, including the 22.5-billion gallon Cobble Mountain Reservoir, the biggest water body in the state second only to the Quabbin Reservoir (Boston water supply). Home to nearly 100,000 residents, the population density across the whole basin is 193 persons/sq. mile, which is divided starkly into distinctly rural (upper reaches of the watershed) and distinctly urban areas (southeastern portion of the basin). The majority of the population (~82%) is centered in the cities of Springfield, West Springfield, Agawam, and Holyoke – which comprise about 18% of watershed area (Pioneer Valley Planning Commission 2006). The average annual flow at USGS gage #01183500, located near the outlet of the watershed with a contributing drainage area of approximately 1,287 km^2, from 1915-2013 is 27 cms (953.2 cfs).

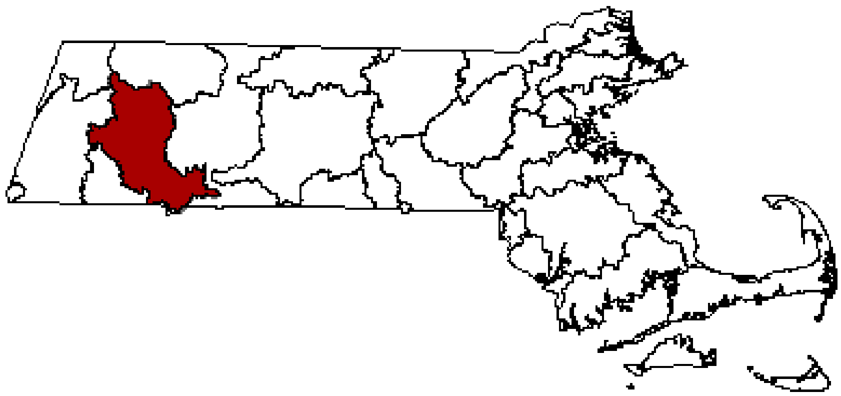

Figure 2: HUC 8 Map of Massachusetts (Westfield Basin shaded in red)

2.3.2 Milwaukee Basin

The Milwaukee River Basin discharges into Lake Michigan and is approximately 2,220 km^2 in area. The Milwaukee Basin is comprised of six sub-basins: Cedar Creek, Kinnickinnic River, Menominee River, Milwaukee River East-West, Milwaukee River North, and Milwaukee River South. The basin encompasses a population of about 1.3 million people. The city of Milwaukee is located at the basin outlet, contributing to the high population density in the southern portion of the basin (approximately 90% of the population resides in the basin's southern quarter). Land in the northern half of the basin is predominately in agricultural use. There are about 600 miles of perennial streams and about 450 miles of intermittent streams in the Milwaukee river basin. A majority of this aquatic habitat is suitable for warm water fish, with only 12% capable of supporting cold water fish communities (Wisconsin Department of Natural

Resources 2001). The approximate average annual flow at the outlet (USGS gage #04087000 in Milwaukee) for a drainage area of 1,802 km^2 is 12.8 cms (451.1 cfs).

Figure 3: HUC 8 Map of Wisconsin (Milwaukee Basin shaded in red)

2.4 Stream Temperature and Resource Management

2.4.1 Structured Decision Making

Structured Decision Making (SDM) is "the collaborative and facilitated application of multiple objective decision making and group deliberation methods to environmental management and public policy problems" (Gregory et al. 2012). It aids and informs decision makers and supports their ability to effectively apply decision theory and risk analysis. Supporters of SDM describe it as a comprehensive, clear, transparent, and defensible framework for understanding and generating alternatives for complex decisions. Both the USGS and U.S. Fish and Wildlife Service (USFWS) have extensively employed SDM and provide training in its application. Additionally, these agencies have integrated SDM into Adaptive Resource Management (ARM), creating a protocol for implementing SDM in decisions iterated over time for long-term responsive resource management as well linked decisions.

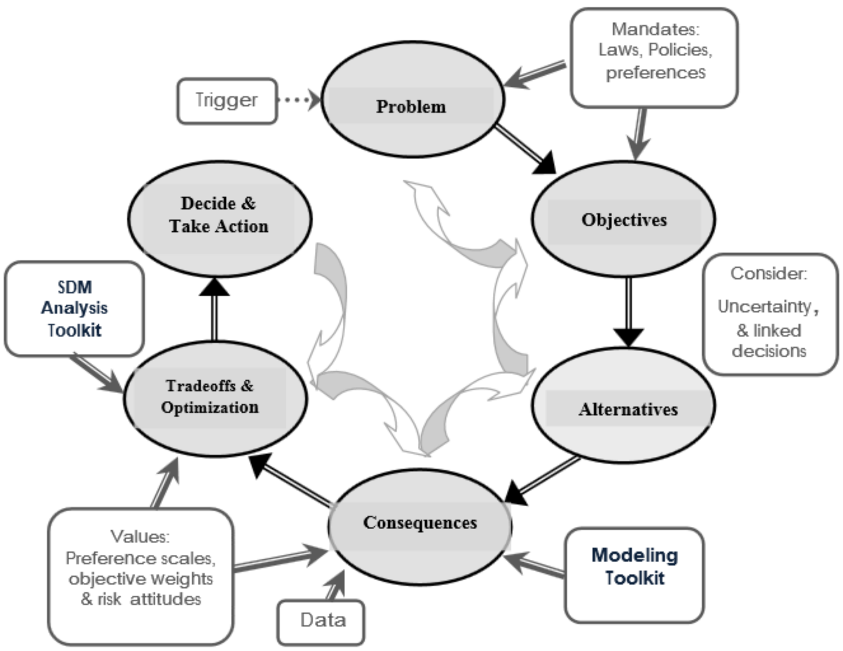

Figure 4: Structured Decision Making Steps (from USFWS, 2008)

The application of SDM requires addressing the following seven questions: 1) What is the context, scope, and/or bounds of the decision?; 2) What objectives and performance measures will be used to evaluate alternatives?; 3) What alternative actions or strategies are being considered?; 4) What are the expected consequences of these respective actions or strategies?; 5) What are the important uncertainties and how do they impact management choices?; 6) What key trade-offs among consequences are there?; and 7) How can the decision be implemented in a way that promotes learning over time and provides opportunities for adaptive management (Gregory et al. 2012)? Modeling is an important part of understanding the consequences of different alternatives, which are used to develop and understand trade-offs (Figure 4). The modeling tools that support the SDM process are incorporated into this stream temperature model comparison, as a means of streamlining the process for resource managers and ensuring the most suitable modeling results are obtained for specific applications.

This research uses an SDM framework to promote efficient and effective decision making for stakeholders concerned with climate change impacts on stream temperature in the northeast. As SDM is highly utilized in natural resource management, it is appropriate to apply it to this research. This framework addresses the management decisions that need to be made, data availability, and model output needs. In order to establish an understanding of stakeholder needs, a survey was developed for resource managers. The results of this survey were used to develop the assessment criteria applied to the three stream temperature models.

The electronic survey was distributed to the NESC's network of professionals working with stream temperature. Twenty-seven responses were received primarily from employees of state agencies (~41%), federal agencies (~30%), and academia (~19%). Two responses were received from local government employees and one response from a non-profit. The majority of responders' field of expertise was aquatic/fisheries biology or ecology (~63%), followed by water or natural resource management (~19%). Two responders identified engineering as their field of expertise, with terrestrial biology or ecology, policy, and hydrology/biogeochemistry identified as the field of expertise for one respondent each. When asked to identify the stream temperature format most important to their resource management decisions, 12 responded spatial watershed-wide snapshots, 8 responded time-series at specific locations, 1 replied both spatial snapshots and time-series, and 5 responded "other". Of the 18 responses for the least dense stream temperature network acceptable for decision making, 72% chose 5km (6 responses) or 10km (7 responses), with ~22% (4) selecting 25km and 1 selecting 50 km – indicating a need for more dense stream temperature networks. The majority (16 responders) selected mean as the most important stream temperature statistic for their work, with 10 selecting maximum (1 did not select an answer). When asked to rank the importance of hourly, daily, monthly, seasonal, and annual time-steps for stream temperatures, ~48% ranked hourly as the most important and ~26% ranked daily as the most important. Approximately 44% ranked daily as the second most important stream temperature time-step. These rankings indicate a need for high temporal resolution. Summer (June, July, August) was identified as the season of greatest management concern by 19 respondents (~70%), 5 chose all seasons, 2 selected spring (March, April, May), and no respondents selected fall (September, October, November) or winter (December, January, February). This is consistent with significant concerns among resource managers regarding maximum lethal temperatures of aquatic species. When asked to rank the importance of specific river scales for their resource management work (headwaters, tributaries, mainstem, outlet), ~41% ranked headwaters as the most important; ~30%, ~19%, and ~1% ranked tributaries, mainstem, and outlet as the most important (respectively). Headwaters were ranked second in order of importance by ~22% of respondents and tributaries were ranked second most important by ~56% of participants. This research responds to a clearly articulated need (of resource managers) for stream temperature models with appropriate spatial and temporal resolutions, model skill, and ease of implementation. These survey results were used to develop the model assessment metrics outlined in the following section.

2.4.2 Assessment Metrics

This research assesses a series of temperature models based on a consistent set of metrics chosen to characterize the model's function and the model's applicability. These metrics are: model skill, data input requirements, spatial and temporal resolution of modeled output, and "user friendliness" (Table 4). The model's skill or ability to accurately estimate water temperature is the metric of interest related to quantitative, statistical measures of model accuracy and are evaluated using Nash-Sutcliffe efficiency (NSE) and normalized root-mean-square error (RSR). RSR is the ratio of the root mean square error to the standard deviation of observed data. The simulated hydrology of VIC and SWAT will also be evaluated using NSE and RSR, as well as percent bias (PBIAS). NSE ranges from $-\infty$ to 1, with 1 being ideal. RSR ranges from 0 to ∞, with 0 being ideal. For PBIAS, a negative value indicates that the model is underestimating, a positive value indicates overestimating, and 0 indicates a perfect estimate. In accordance with the guidelines Moriasi et al. (2007) for calibrating hydrologic models, the threshold of successful calibration for each statistic is as follows: NSE > 0.5, RSR ≤ 0.7, and PBAIS between $\pm$ 25%.

Table 4: Model Performance Statistics (from Cambell et al., 2011)

Measure	Abbreviation	Description	Mathematical Definition
Nash-Sutcliffe Efficiency	NSE	Variation of measured values accounted for in the model	$1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}$
Normalized Root Mean Square Error	RSR	Ratio of the root-mean-square error and standard deviation of observed values	$\frac{\sqrt{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}}{\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$
Percent Bias	PBIAS	Difference between observed and simulated values expressed as a percent	$\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)}{\sum_{i=1}^{n}(Y_i)} \times 100$

Data requirements are given a qualitative ranking of low, medium, or high. The spatial and temporal resolution metrics will be presented numerically. For the highly qualitative "user friendliness" metric, an ordinal ranking of 1 to 3 will be given (with 1 being the most user friendly model).

In addition to providing background on the role of stream temperature in aquatic ecosystems, this chapter discussed decision-making in the context of natural resource management and gave a history of water quality modeling (specifically regarding temperature). The models are reviewed in Chapter 3 and ranked and Chapter 4.

3. Model Review

In this research, the VIC-RBM, SWAT-Ficklin et al. (2012), and Mohseni et al. (1998) nonlinear regression models are applied to each of the study basins (the Westfield and Milwaukee) and assessed according to the metrics outlined in Chapter 2. This chapter presents observations and details from implementing the models for the study basins, which will be synthesized into an assessment of the models presented in Chapter 4.

3.1 Data

3.1.1 USGS Flow Data

Streamflow data used in this research were obtained from the USGS GAGES-II (Geospatial Attributes of Gages for Evaluating Streamflow) database (Falcone 2011). This database, released in 2011, is an updated version of the original GAGES database developed by the USGS National Water-Quality Assessment (NAWQA) Program that was published in 2010. USGS flow gages were selected for inclusion according to criteria designating them as being minimally affected by direct human activities. Flow gages presented in Table 5.

Table 5: Hydrology Calibration Gages

Basin	USGS ID	Name	Latitude	Longitude
Westfield	01181000	West Branch Westfield River at Huntington, MA	42.237312	-72.895654
Milwaukee	04086600	Milwaukee River near Cedarburg, WI	43.280283	-87.942866

3.1.2 Stream Temperature Data

Stream temperature observations for the Westfield basin were collected by the Massachusetts Department of Environmental Protection. Data was sub-daily (one-hour intervals) and was aggregated into daily average stream temperatures. Data site “MAKear55” was used for calibration due to its long period of record (Table 6). Stream temperature observations for the Milwaukee basin come from the Wisconsin Department of Natural Resources (DNR). The site chosen for calibration was the Menominee River at Menominee station (site ID #04087030), located in a cool-warm headwater stream. It was chosen for both the long period of record and its proximity to the USGS flow gage used for calibration (Table 6).

Table 6: Temperature Data Sites

Site (Basin)	Latitude	Longitude	Period of Record
MAKear55 (Westfield)	42.43621	-72.92976	7/21/2005 – 4/15/2008
Menominee River @ Menominee (Milwaukee)	43.1728	-88.1039	11/8/2008 – 11/12/2013

3.2 VIC-RBM

3.2.1 Implementation and Model Skill

The Connecticut River VIC model (which includes the Westfield basin) was calibrated prior to this study (Polebitski et al. 2012). The daily streamflow for the Westfield basin was calibrated to a Nash-Sutcliffe Efficiency value of 0.54, with peak flows typically under-simulated. The modeled average annual flows have a -7.5% bias compared with observations, with a root mean square error (RMSE) of 252 cfs over the calibration period (135% of the average flow for the time period).

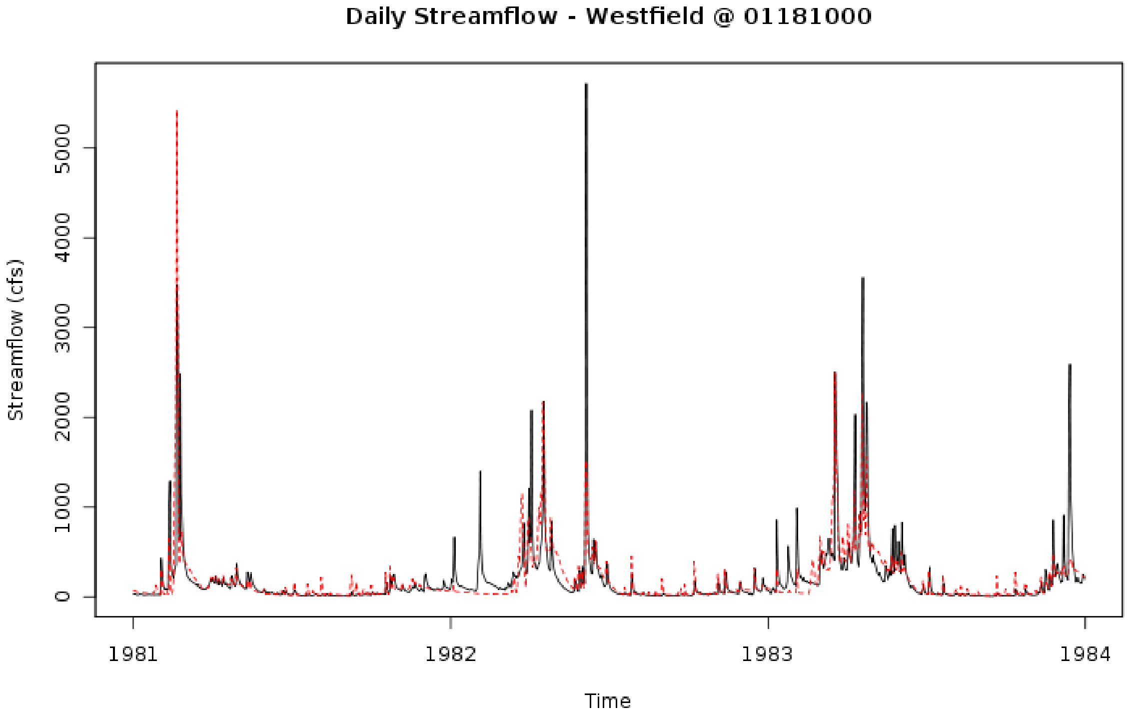

Figure 5: Daily Streamflow (from Polebitski et al. 2012)

The RBM model was calibrated to a NSE of 0.772 for the calibration period (1/1/2007 – 4/15/2008) and a RSR of 0.478. This yielded a NSE 0.684 and a RSR of 0.593 for the validation period (7/21/2005 – 12/31/2006) for the Westfield basin. The combined calibration and validation periods has a NSE of 0.721 and a RSR of 0.528.

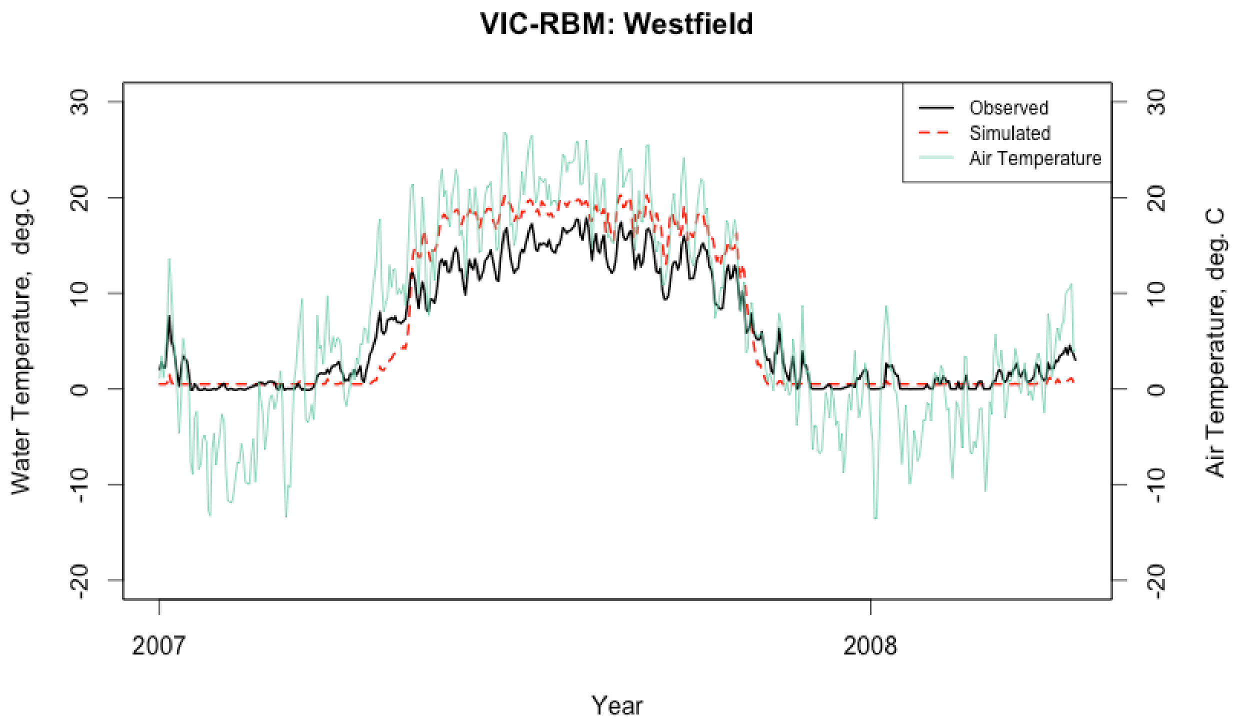

Figure 6: VIC-RBM Stream Temperature Calibration Period

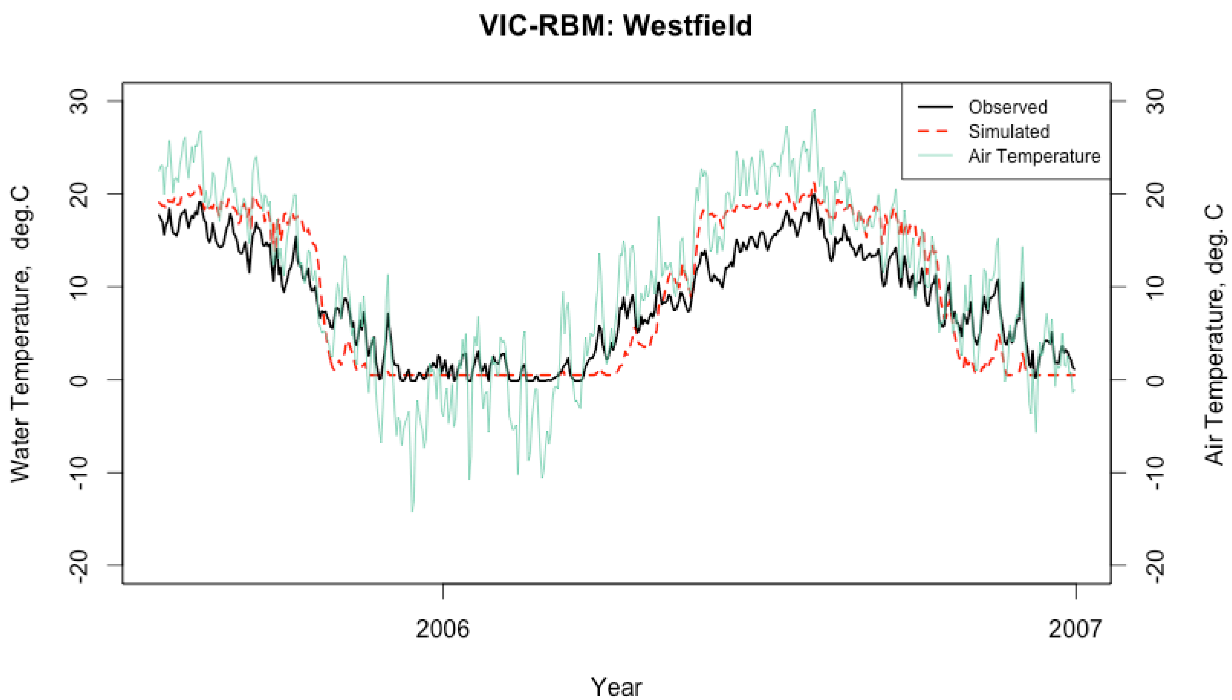

Figure 7: VIC-RBM Stream Temperature Validation Period

In the VIC-RBM calibration and validation plots, the following can be noted. First, there is potentially some over-calibration: in the validation period, VIC-RBM simulates rapid decreases in water temperature in the fall months (2006 and 2007) that are uncorrelated with observed temperatures. When examining the calibration period, the observed water temperatures exhibit a steep decline in the fall that the model is capturing very well. Over-calibration can partially be explained by the lack of data available for calibration and validation. Another notable model output characteristic is that the spring water temperature predictions are consistently too high relative to the observations. These model output patterns are consistent with those observed by van Vliet et al. (2012) in the Lena basin (in Russia). The VIC-RBM output for that basin exhibited a falling limb during August-October that is too rapid and the decrease begins too soon. It was also observed that VIC-RBM over estimated spring water temperatures, as the model was not accounting for ice and meltwater inflow.

3.2.2 Data Input Requirements

Data requirements for VIC-RBM include: precipitation, maximum air temperature, minimum air temperature, and wind speed files which have been developed nationally and are available as gridded meteorological datasets (Maurer et al. 2002). These datasets are periodically updated; version 5.7.2.14 (08/19/2009) was used in this research. Additional parameter files include soil, vegetation, vegetation library, and snowband files. A flow direction file must be developed to route flows between grid cells. The RBM model requires output from the Mohseni et al. (1998) nonlinear regression model to provide boundary conditions for headwater temperatures.

3.2.3 Spatial and Temporal Resolution

The VIC model is a "Continental" scale model, originally designed to simulate hydrological processes in very large river systems. The limiting factor in spatial resolution is the availability of high-resolution gridded input data. This work was performed using 1/8 degree gridded data (~12.5 km) meaning VIC-RBM simulates one temperature per grid cell (~140km^2). Recently, 1/16 degree gridded data sets have become available, creating the potential for increased spatial resolution (Livneh et al. 2013).

The VIC-RBM extends the VIC model by simulating mean daily water temperatures. The VIC model is capable of computing sub-daily energy fluxes at a 3-hour time-step, which may potentially be incorporated into future versions of RBM. For this research, the model was applied at a spatial resolution of 1/8 degree with a mean daily water temperature temporal resolution.

3.2.4 User Friendliness

The VIC-RBM model operates in a Linux environment. It was developed as a research tool, and thus, assumes a high level of experience in modeling hydrologic processes. Computer coding experience is required for implementation and trouble-shooting. The VIC-RBM model lacks a visual-oriented user-interface, and as such is not ideal for engaging stakeholders in the modeling process.

3.2.5 Summary Table

A summary of the VIC-RBM model performance according to the performance metrics is presented in Table 7.

Table 7: Summary of VIC-RBM Metrics

Metric	Summary	
Skill (Validation)	NSE: 0.648	RSR: 0.593
Data Requirements	Gridded meteorological data and parameter files, flow direction file, Mohseni parameters	
Spatial Resolution	1/8 degree (~140 km^2 area)	
Temporal Resolution	Mean daily water temperature	
User Friendliness	Requires high degree of modeling knowledge	

3.3 SWAT-Ficklin et al. (2012)

3.3.1 Implementation

ArcSWAT 2009.93.7b was used for its compatibility with the Ficklin et al. (2012) stream temperature model. Calibrations of both the SWAT hydrology and the temperature model were performed manually. For each basin, the hydrology of the SWAT model was calibrated and validated before progressing to the Ficklin et al. (2012) stream temperature model. The Westfield Basin SWAT hydrology was manually calibrated to a NSE of 0.511 and a RSR of 0.699 for the calibration period (1/1/2001-12/31/2010). The simulated hydrology exhibited a -2.6% bias versus the observations for this period. This yielded a NSE of 0.510, a RSR of 0.700, and a PBIAS of -8.7% for the validation period (1/1/1990-12/31/2000). For the entire period of record (1/1/1990-12/31/2010) this resulted in a NSE of 0.511 and a RSR of 0.699. The PBIAS versus the observations was -5.7%.

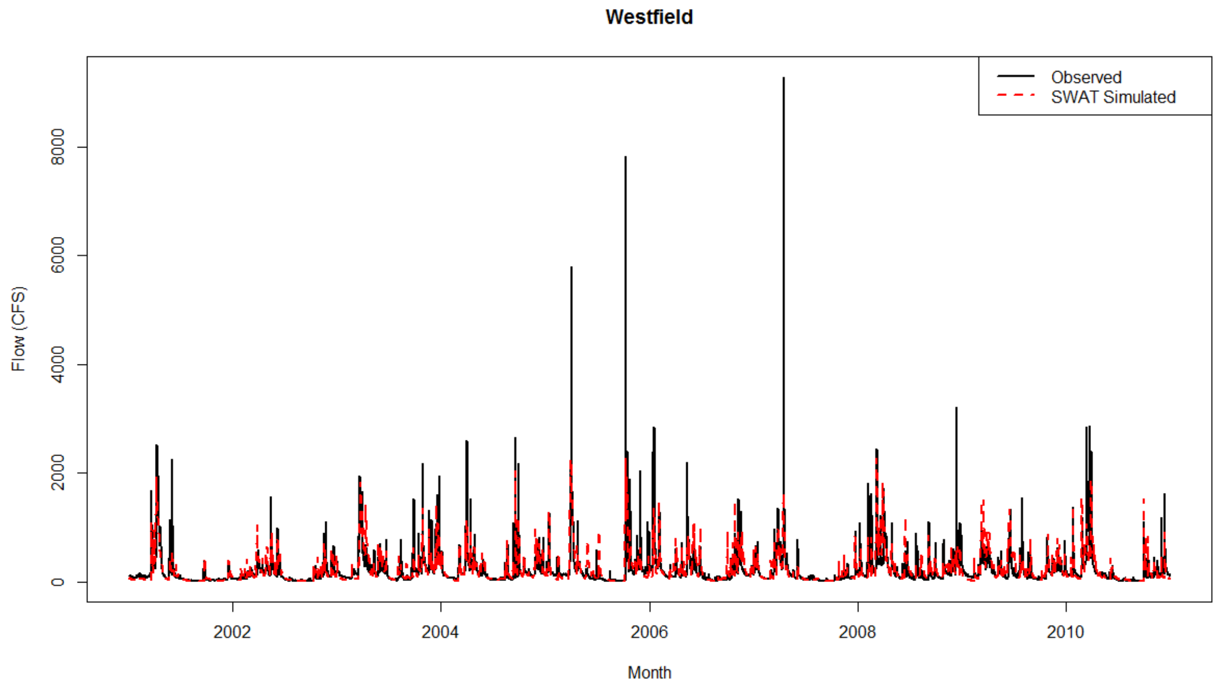

Figure 8: SWAT Hydrology Calibration, Westfield

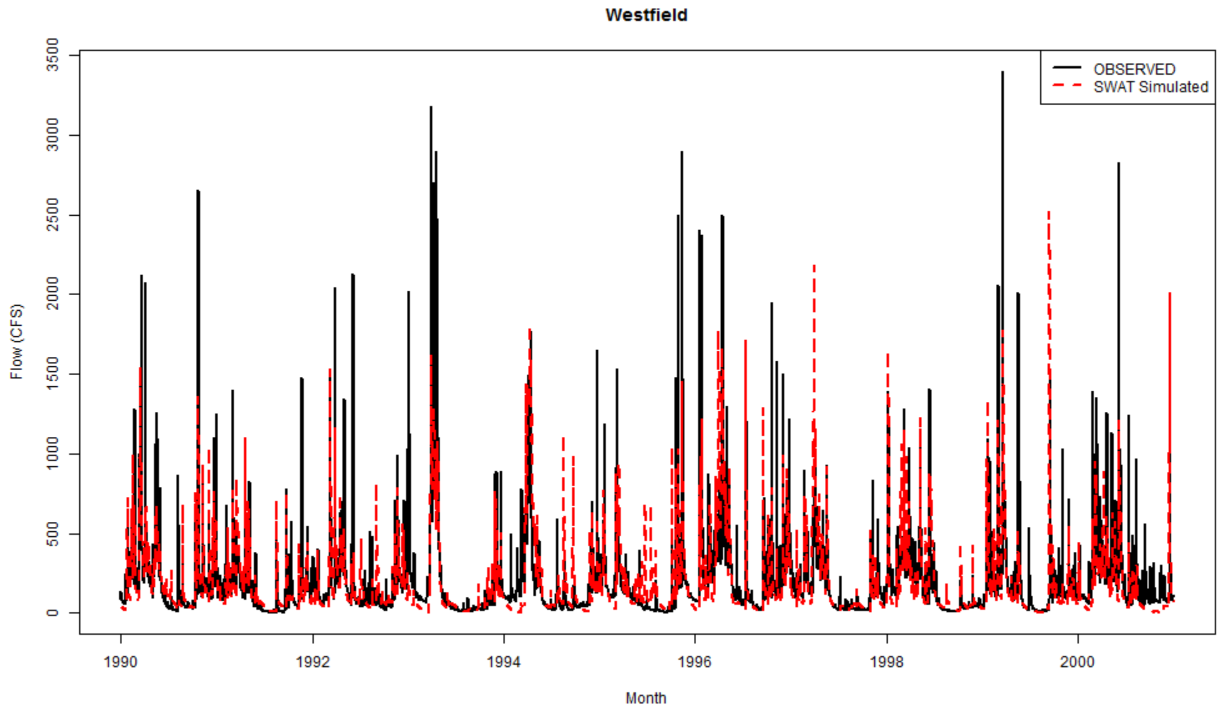

Figure 9: SWAT Hydrology Validation, Westfield

The water temperature was calibrated to an NSE of 0.935 and an RSR of 0.256 for the calibration period from 1/1/2007 – 4/15/2008. The validation period (7/21/2005 – 12/31/2006) yielded an NSE of 0.664 and an RSR of 0.579. This yielded an overall NSE of 0.678 and RSR of 0.567.

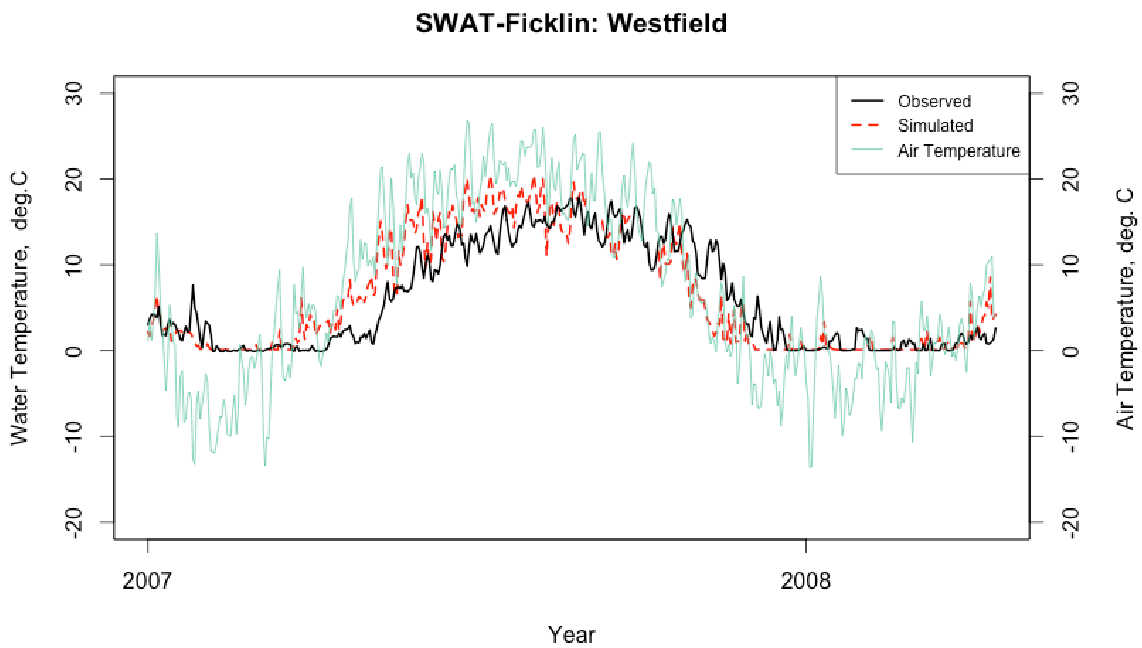

Figure 10: SWAT-Ficklin et al. (2012) Temperature Calibration, Westfield

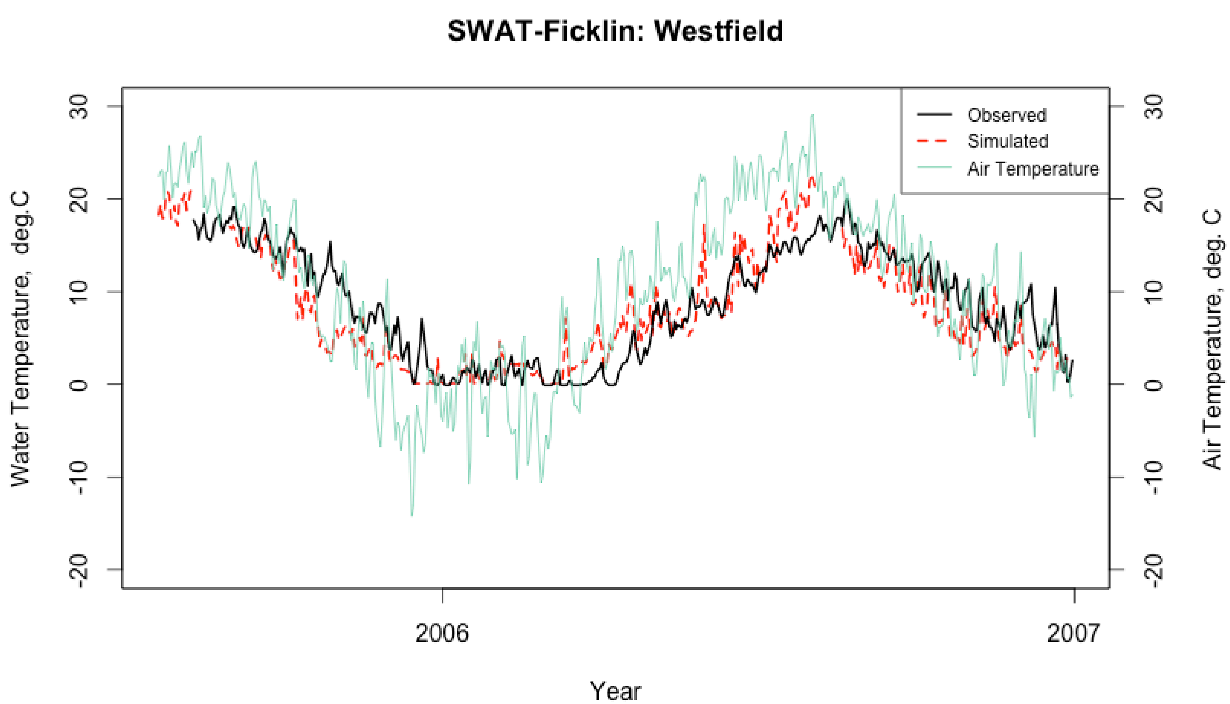

Figure 11: SWAT-Ficklin et al. (2012) Temperature Validation, Westfield

The SWAT hydrology for the Milwaukee Basin was manually calibrated to a NSE of 0.465 and a RSR of 0.731 for the period 1/1/2001-12/31/2010. The simulated hydrology exhibited a -1.6% bias versus the observations for this calibration period. The validation period (1/1/1990-12/31/2000) yielded a NSE of 0.472, a RSR of 0.726, and 13.8% bias. For the period of record (1/1/1990-12/31/2010), the model had a NSE of 0.469 and a RSR of 0.729. The PBIAS was 6.1%.

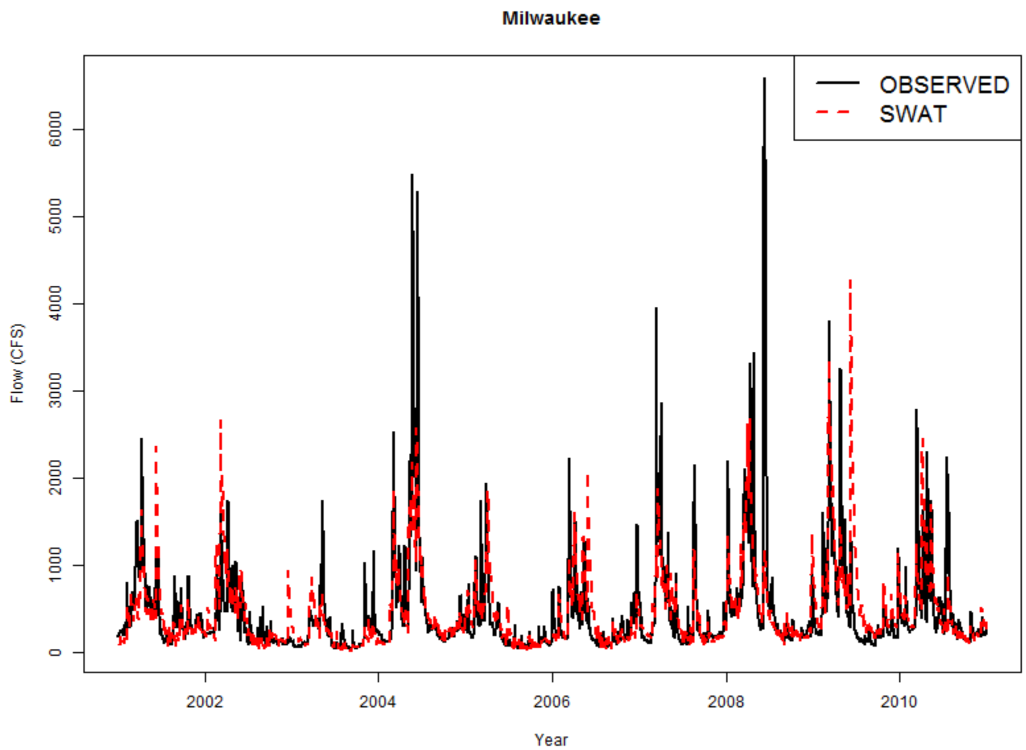

Figure 12: SWAT Hydrology Calibration, Milwaukee

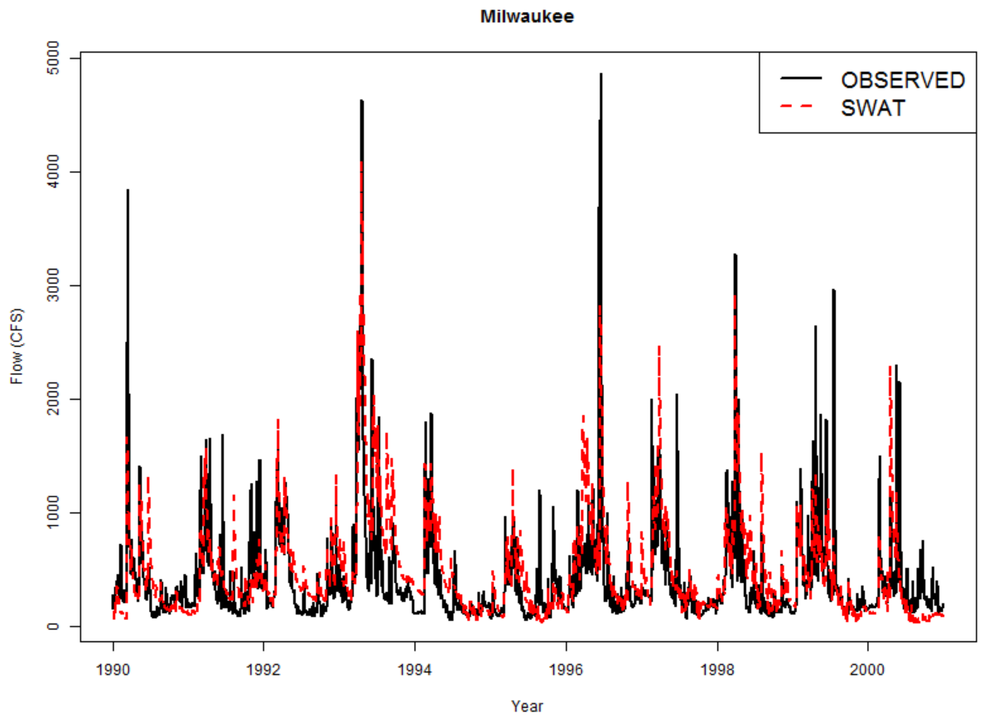

Figure 13: SWAT Hydrology Validation, Milwaukee

The water temperature was calibrated to a NSE of 0.896 and a RSR of 0.322 for the period from 11/8/2008-12/31/2009. The validation period (1/1/2010-12/31/2010) yielded a NSE of 0.910 and a RSR of 0.300. For the entire period of record (11/8/2008-12/31/2010) the overall NSE was 0.904 and the RSR was 0.309.

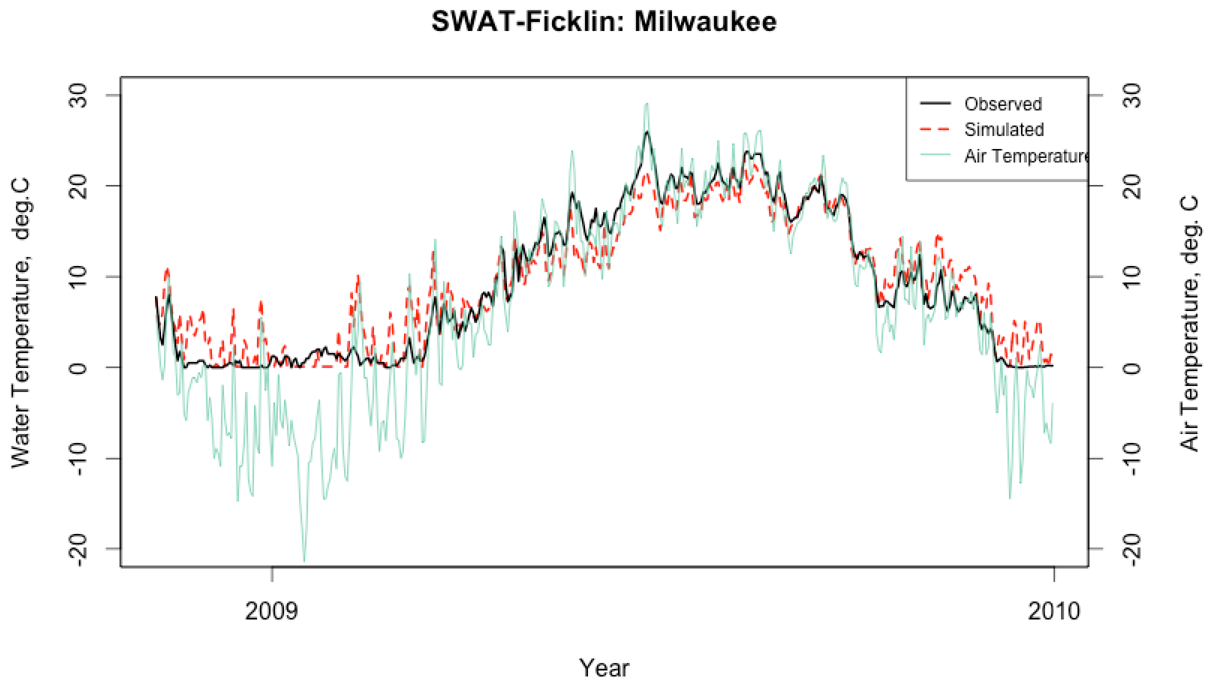

Figure 14: SWAT-Ficklin et al. (2012) Temperature Calibration, Milwaukee

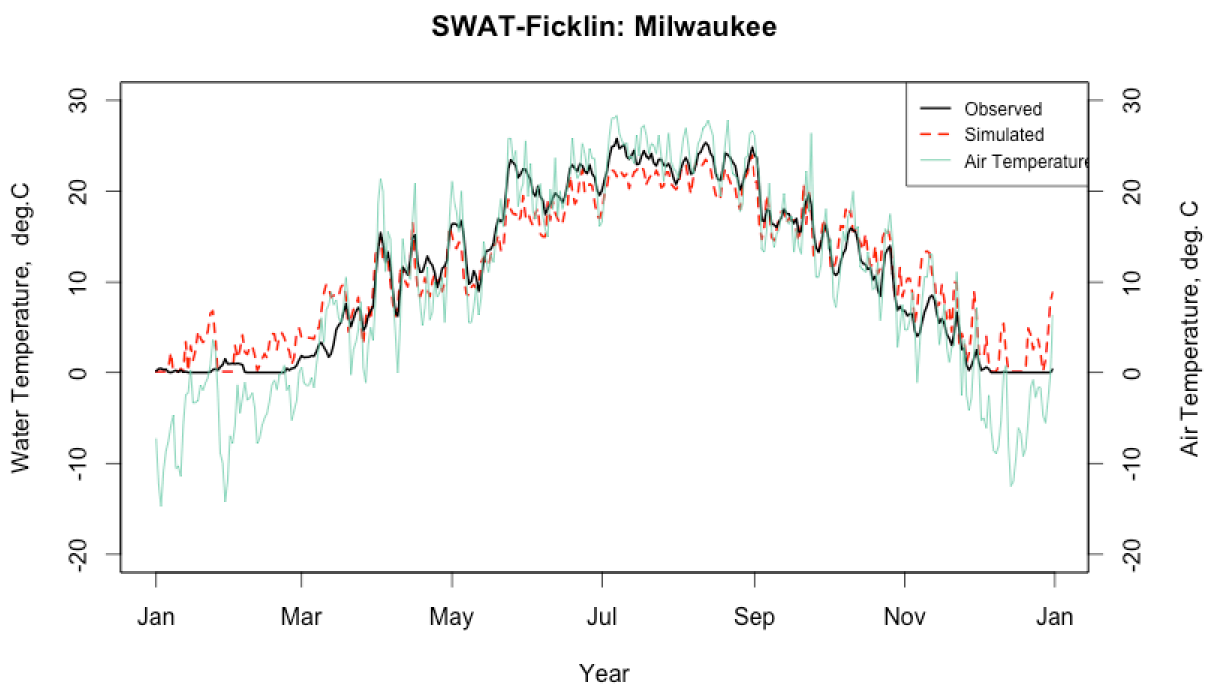

Figure 15: SWAT-Ficklin et al. (2012) Temperature Validation, Milwaukee

3.3.2 Data Input Requirements

The ArcSWAT interface for the SWAT-Ficklin model utilizes publicly available spatial datasets to delineate the watershed of interest, as well as smaller subbasins and even smaller Hydrologic Response Units (HRUs). Digital Elevation Models (DEMs) were obtained from the National Hydrography Dataset Plus (NHDPlus) website. The Version 2 HydroDEM was used for the Westfield basin, whereas the Version 1 DEM was used for the Milwaukee due to SWAT incompatibility issues. Land use spatial data was obtained from the National Land Cover Dataset (NLCD) – with the most recent data used for both basins. The most recent STATSGO soils data was obtained from the USDA Geospatial Data Gateway. Weather observation inputs to the model include precipitation, air temperature, relative humidity, solar radiation, and wind speed. These data are available as a gridded data set through the SWAT website (www.swat.tamu.edu) and is provided by the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR).

3.3.3 Spatial and Temporal Resolution

SWAT is a landscape-scale hydrological model. The spatial resolution in SWAT varies according to the specific watershed being analyzed, but was similar for the Westfield and Milwaukee basins. The Ficklin et al. (2012) model is able to produce a stream temperature for every individual reach within the SWAT hydrologic model. SWAT delineated 113 stream reaches (~451 km of river) in the Westfield, producing on average one temperature per every 4 km of river mile (or 12 km^2 of watershed area). The larger Milwaukee basin was delineated into 123 stream reaches (~679 km of river), producing one temperature per every 5.5 km of river mile (or 18 km^2 of watershed area) on average. It is important to note, the Ficklin et al. (2012) stream temperature model is unable to calculate water temperatures when the flow in a stream is less than 0.01 cms. Like the VIC-RBM model, the SWAT-Ficklin et al. (2012) model simulates mean daily streamflows and mean daily water temperatures.

3.3.4 User Friendliness

The SWAT-Ficklin et al. (2012) model has an excellent visual user-interface (through ArcGIS), allowing for visual demonstrations with stakeholders. The geospatial data needed for implementation is readily available and easy to acquire. The time and difficulty involved in calibration differs significantly from one basin to the next according to size and watershed complexity. The calibration process can be made much simpler by the use of an automated calibration software package. The program is designed to be applied by individuals without a great deal of programming experience.

3.3.5 Summary Table

A summary of the SWAT-Ficklin et al. (2012) model performance according to the performance metrics is presented in Table 8.

Table 8: Summary of SWAT-Ficklin et al. (2012) Metrics

Metric	Summary			
	Westfield		Milwaukee	
Skill (Validation)	NSE: 0.664	RSR: 0.579	NSE: 0.910	RSR: 0.300
Data Requirements	Spatial data (DEM, land use, soils) and meteorological data			
Spatial Resolution	~4 km of river/ ~12km^2 of watershed area		5.5 km of river/ 18km^2 of watershed area	
Temporal Resolution	Mean daily water temperature			
User Friendliness	Easily acquired data inputs paired with excellent visual user-interface. Calibration can be difficult.			

3.4 Mohseni et al. (1998) Nonlinear Regression

3.4.1 Implementation

Mohseni et al. (1998) presents a temperature modeling approach based on a nonlinear regression model. This has been implemented and calibrated/validated using R statistical software, with an optimizing function to determine the best fit for the four parameters – α, β, μ, θ – using the Shuffled Complex Evolution (SCE) method (Duan et al. 1993). The Westfield basin was calibrated to an NSE of 0.956 and a RSR of 0.209 for the period 1/1/2007 – 4/15/2008. The validation period (7/21/2005 – 12/31/2006) yielded a NSE of 0.931 and a RSR of 0.262. This resulted in a NSE of 0.946 and a RSR of 0.233 for the combined calibration and validation period.

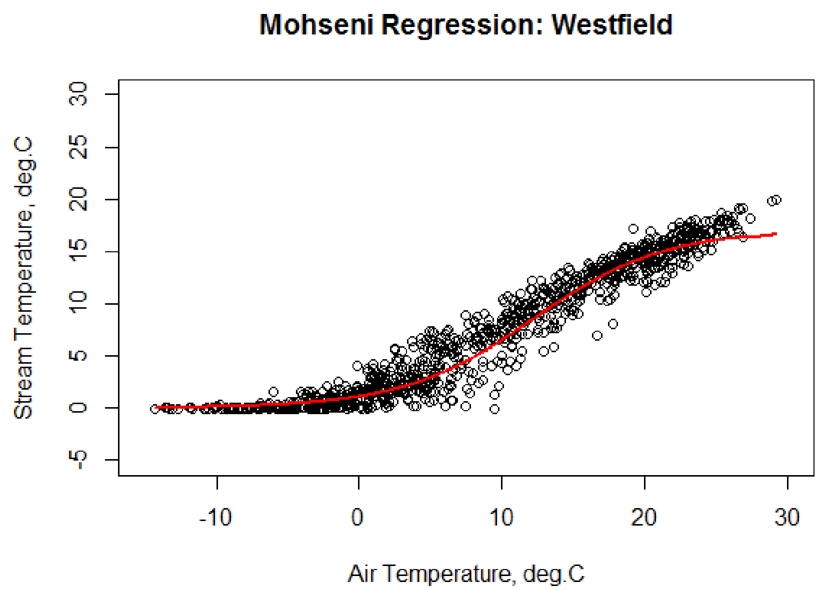

Figure 16: Mohseni S-shaped Regression, Westfield Basin

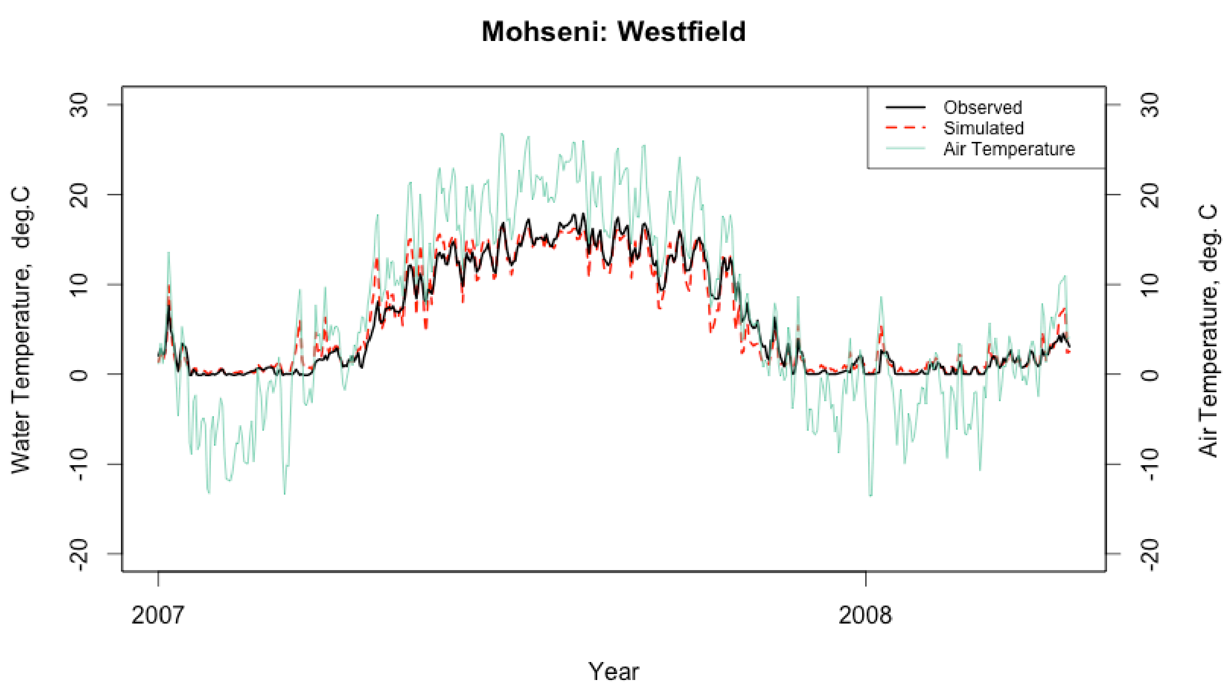

Figure 17: Mohseni et al. (1998) Calibration, Westfield

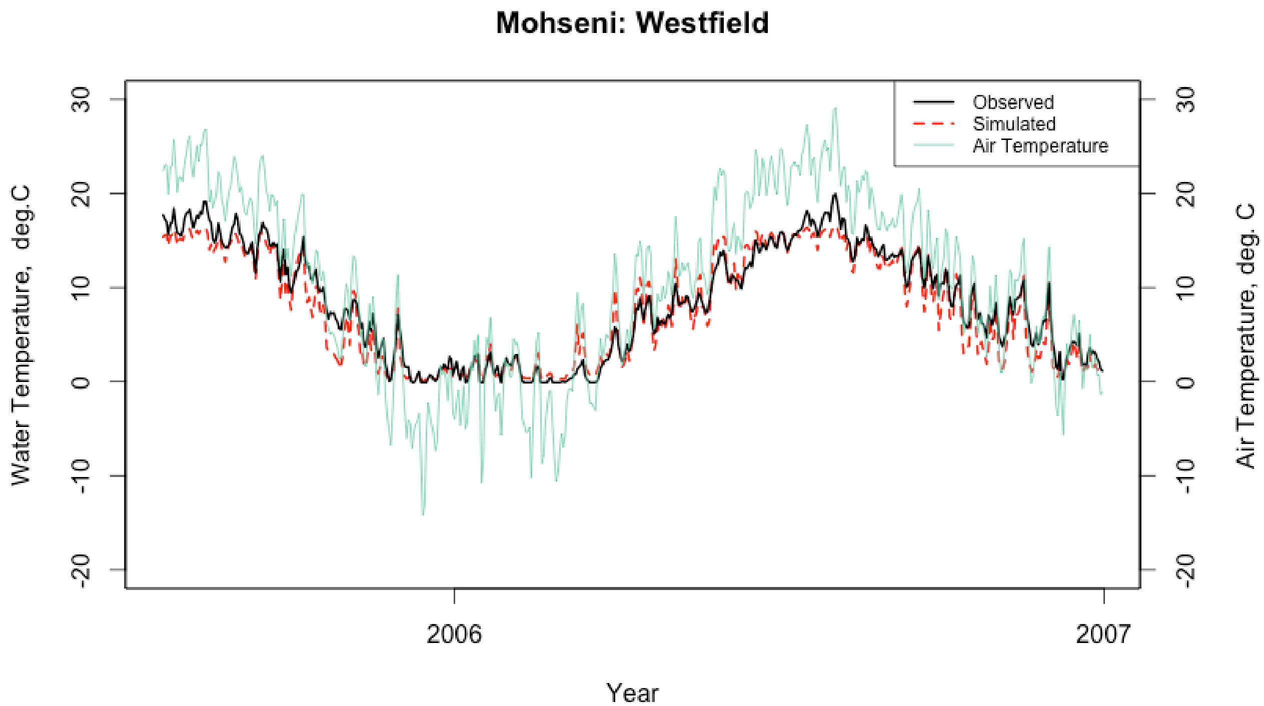

Figure 18: Mohseni et al. (1998) Validation, Westfield

For the Milwaukee basin, the model was calibrated to a NSE of 0.946 and RSR of 0.231 for the period 11/8/2008-12/31/2009. The validation period (1/1/2010 – 12/31/2010) yielded an NSE of 0.945 and an RSR of 0.235. This yielded a NSE of 0.940 and a RSR of 0.245 for the period of record (11/8/2008-12/31/2010). Air temperature data was obtained from the National Climatic Data Center (NCDC) Global Historical Climatology Network (GHCN) Database for site #USC00475474 (located in Milwaukee at Mt. Mary College).

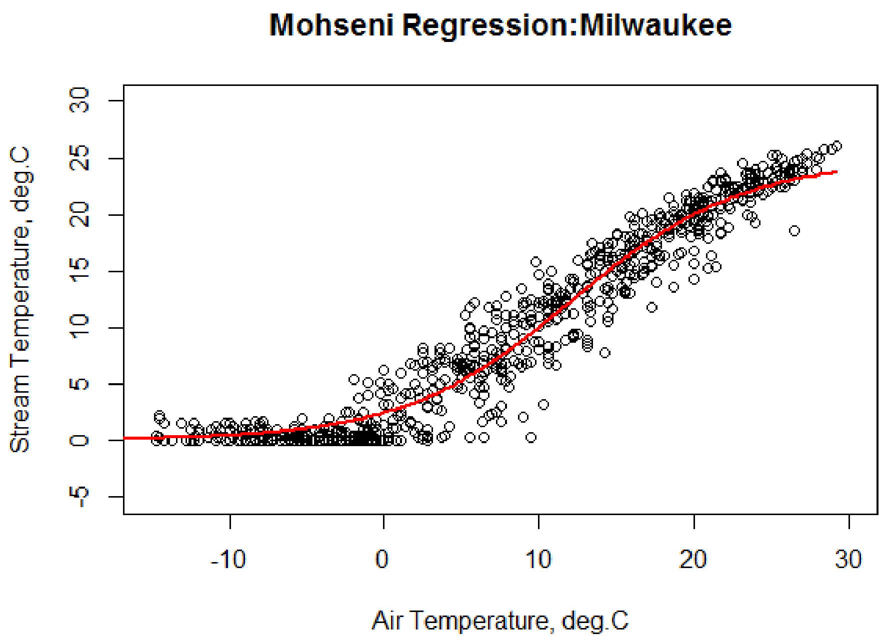

Figure 19: Mohseni S-shaped Regression, Milwaukee Basin

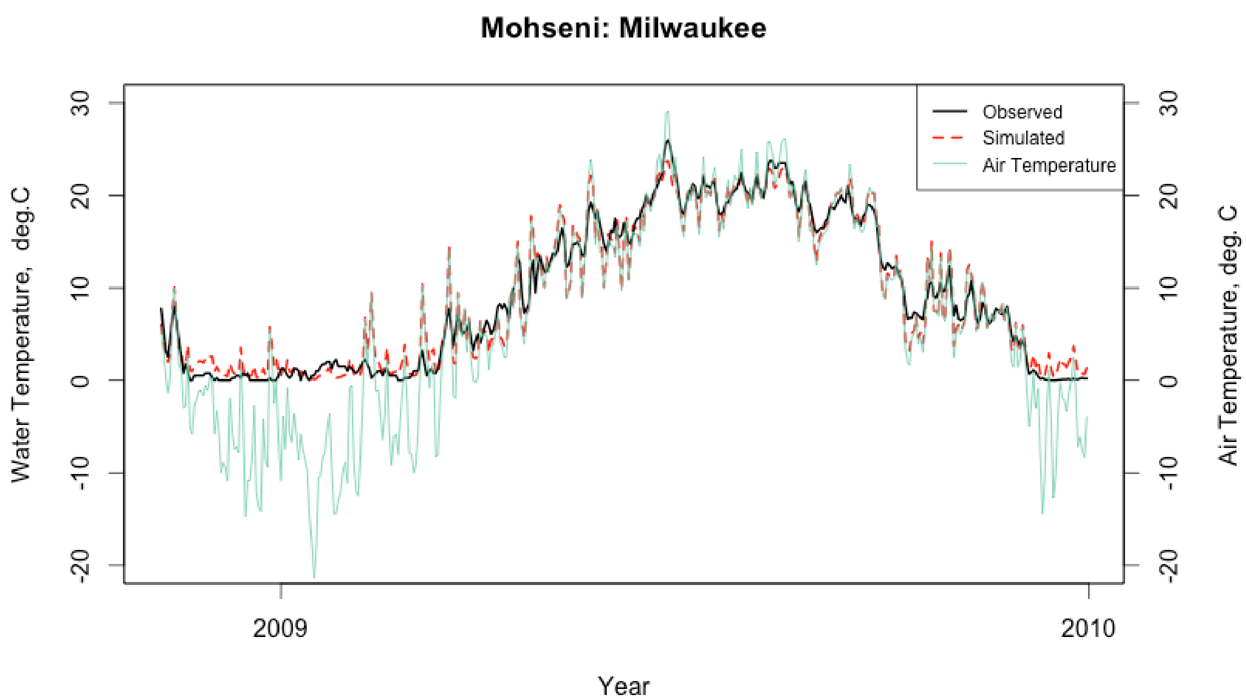

Figure 20: Mohseni et al. (1998) Calibration, Milwaukee

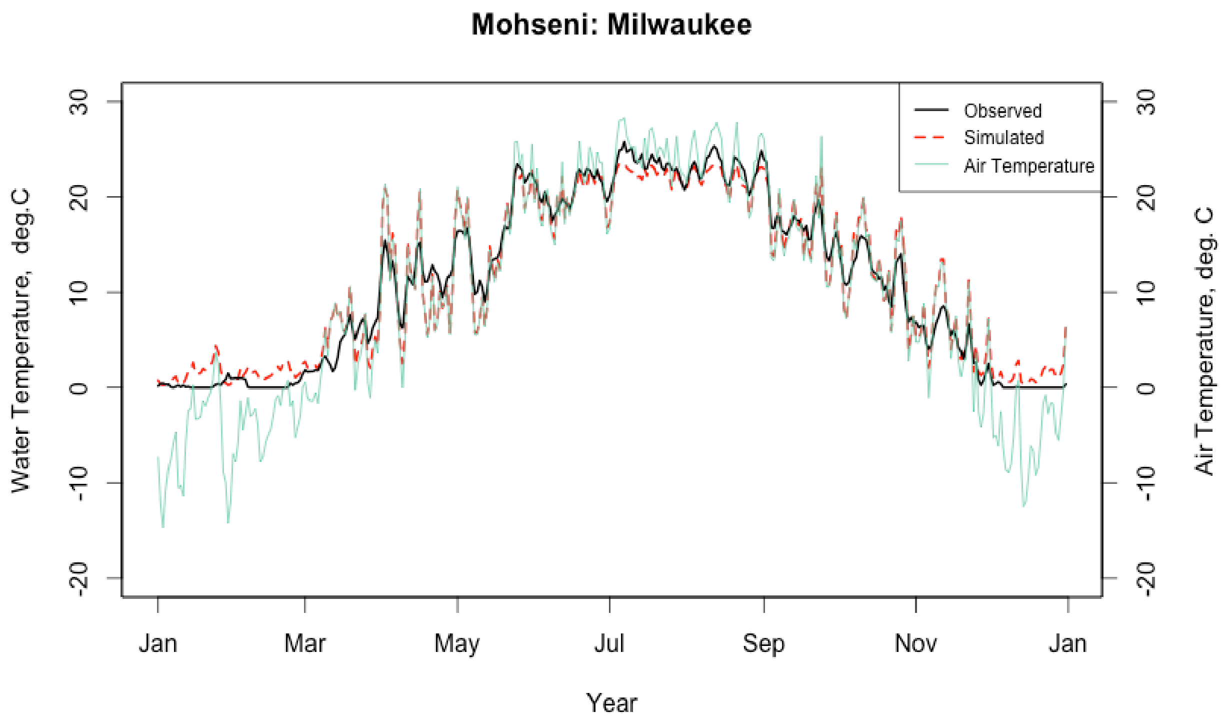

Figure 21: Mohseni et al. (1998) Validation, Milwaukee

3.4.2 Data Input Requirements

To implement the model at a point of interest, one must have stream temperature observations at that location as well as air temperature observations. There is ambiguity as to the period of record necessary to generate a robust regression, but a minimum of 3 years of data is recommended (Mohseni et al. 1998).

3.4.3 Spatial and Temporal Resolution

The Mohseni et al. (1998) nonlinear regression is zero dimensional (0D), meaning temperatures are predicted only at specific sites, with multiple site predictions carried out independently (Caissie 2006). The Mohseni et al. (1998) non-linear regression model cannot be applied to sites that do not exhibit the S-shaped curve relationship between air and water temperature – in the original Mohseni et al. (1998), 1.9% of stations were not well-modeled by the S-shaped curve. The Mohseni et al. (1998) model was developed for predicting weekly mean water temperatures. In this research it was applied on a daily time-step, which is successful in many, but not all locations (Benyahya et al. 2007; Morrill et al. 2005). It is important to note that as the regression model fits data better over longer time scales (originally implemented weekly) the four parameters of the model may vary across different time scales of application. Thus it is recommended that the regression model be re-calibrated when applied to different time scales. The model has been used to predict maximum and minimum weekly stream temperatures (Mohseni et al. 2003) indicating that there may be potential for application on a daily time-step for maximum and minimum stream temperatures.

3.4.4 User Friendliness

The Mohseni et al. (1998) model is very easy to implement with knowledge of statistical software coding and can be executed quite quickly. Complications in implementation may arise with formatting observations for use in the model or insufficient observations of water and air temperatures.

3.4.5 Summary Table

A summary of the Mohseni et al. (1998) model performance according to the performance metrics is presented in Table 9.

Table 9: Summary of Mohseni et al. (1998) Metrics

Metric	Summary			
	Westfield		Milwaukee	
Skill (Validation)	NSE: 0.931	RSR: 0.262	NSE: 0.945	RSR: 0.235
Data Requirements	Stream and air temperature observations for point of interest			
Spatial Resolution	Zero Dimensional			
Temporal Resolution	Max weekly, mean weekly, or mean daily water temperature			
User Friendliness	Easy to implement with statistical computing software			

3.5 Climate Change Analysis

A range of possible future climate scenarios were evaluated with the VIC-RBM, SWAT-Ficklin et al. (2012), and Mohseni et al. (1998) models for the Westfield basin utilizing a method similar to the bottom-up decision-centric method developed by Brown et al. (2012). For this analysis, the precipitation and air temperature inputs to VIC-RBM and SWAT-Ficklin et al. (2012) were altered to reflect possible future situations. Precipitation inputs were based on the original observations used to inform the models and altered by percentages – meaning each daily precipitation amount was altered by the specific percentage. These percentages ranged (in increments of 10%) from 90% of observed to 130% of observed (for a total of 5 different precipitation scenarios). Daily air temperature observations used to inform the models were altered by a number of degrees Celsius (in increments of 1° C) ranging from 0° C to 7° C (for a total of 8 different air temperature scenarios). Each precipitation scenario was combined with each individual air temperature scenario, yielding 40 final scenarios to be evaluated with each model. The scenario of 100% of observed precipitation and 0 ° C air temperature increase was used as a control. As the Mohseni et al. (1998) model does not require precipitation inputs (there is no hydrology component), only the range of air temperature increases were input into the model for analysis.

4. Results

4.1 Model Comparison

This research compares three water temperature models using the following criteria: model temperature prediction skill (NSE and RSR), data input requirements, spatial and temporal resolution of modeled output, and "user friendliness."

The respective skills of these models in predicting stream temperatures in each study basin, as assessed using NSE and RSR, are presented in Table 10, Table 11, and Table 12. Results are presented based upon calibration period, validation period, and the period of record (calibration and validation periods combined). "IP" indicates that work on the particular model is in progress and will be completed in the future by Dr. Austin Polebitski of the University of Wisconsin Platteville.

Table 10: Model Temperature Skill (Calibration)

Model	Westfield Basin		Milwaukee Basin	
	NSE	RSR	NSE	RSR
VIC-RBM	0.772	0.477	IP	IP
SWAT-Ficklin	0.931	0.262	0.896	0.322
Mohseni	0.956	0.209	0.946	0.231

Table 11: Model Temperature Skill (Validation)

Model	Westfield Basin		Milwaukee Basin	
	NSE	RSR	NSE	RSR
VIC-RBM	0.648	0.593	IP	IP
SWAT-Ficklin	0.664	0.579	0.910	0.300
Mohseni	0.931	0.262	0.945	0.235

Table 12: Model Temperature Skill (Combined Calibration and Validation Periods)

Model	Westfield Basin		Milwaukee Basin	
	NSE	RSR	NSE	RSR
VIC-RBM	0.721	0.528	IP	IP
SWAT-Ficklin	0.678	0.567	0.904	0.309
Mohseni	0.946	0.233	0.940	0.245

The Mohseni et al. (1998) model had the best prediction skill of the three models assessed. As a statistical model, the calibration process was simpler and required less time and effort than the two physical models. However, the historical stream temperature datasets available for both the Westfield and Milwaukee basins were not particularly long. Future research should investigate the results of applying the Mohseni et al. (1998) model to settings with longer periods of recorded data. All three models exhibited periods when they dramatically over and under predicted temperatures, and these were often associated with dramatic and rapids changes in the estimates (with the exception of winter stream temperatures predicted by the VIC-RBM model, which were fairly constant at 0° C in the winter).

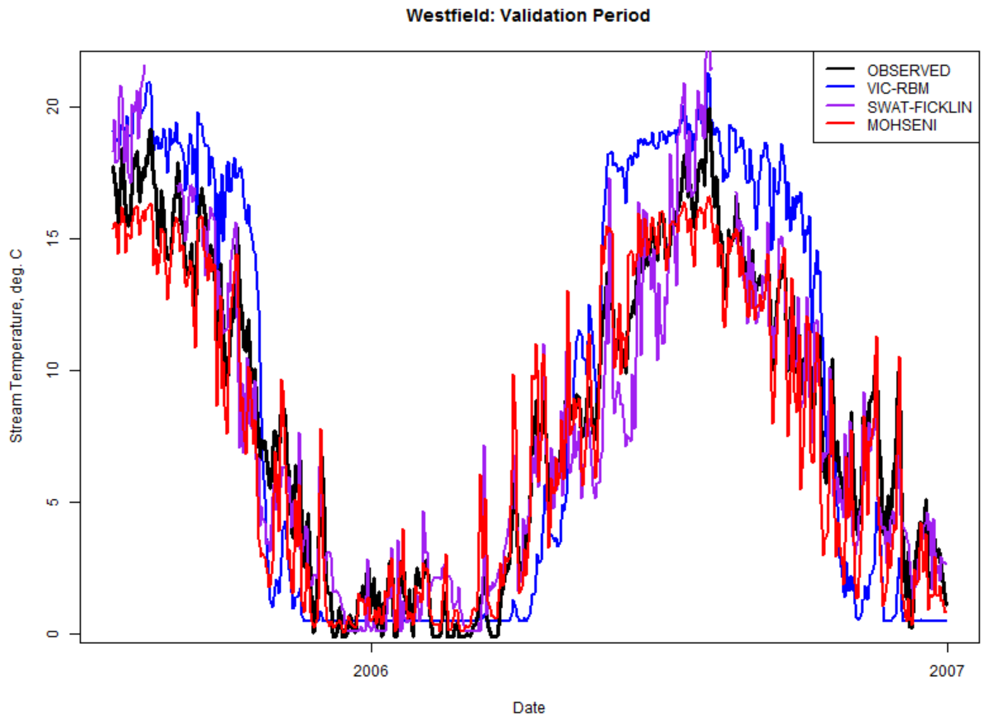

Figure 22: Validation Period of 3 Models, Westfield Basin

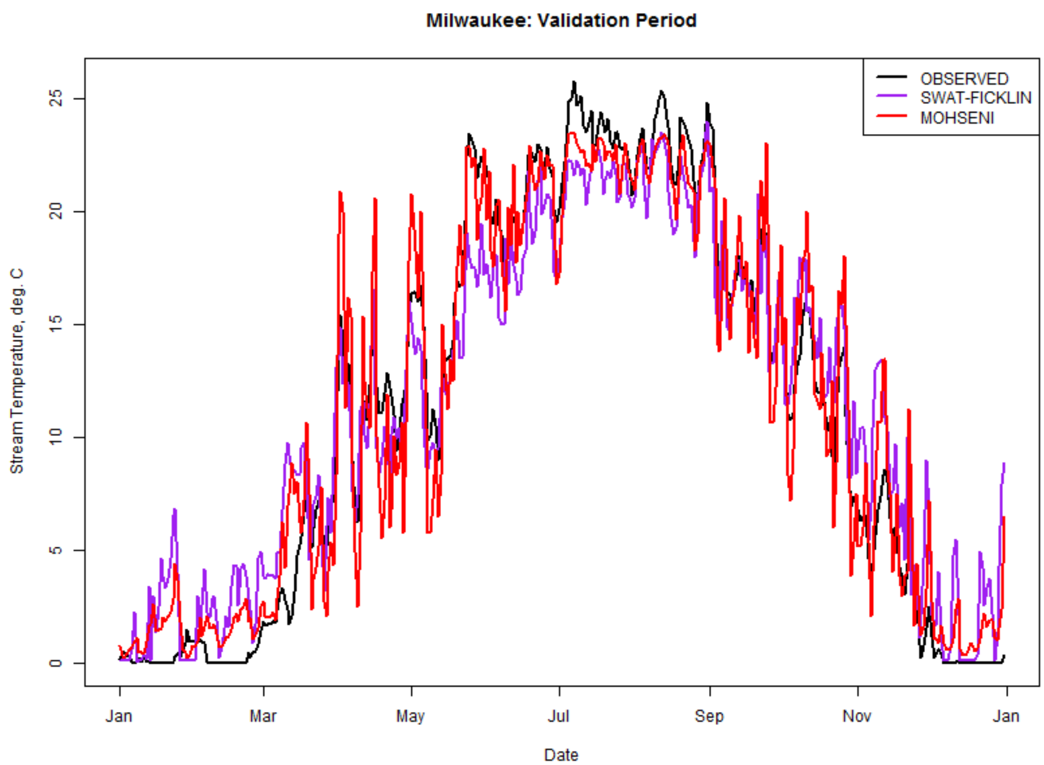

Figure 23: Validation of 2 Models, Milwaukee Basin

VIC-RBM had the greatest data input requirements, followed by the SWAT-Ficklin et al. (2012) model. The Mohseni et al. (1998) model had the lowest data input requirements, needing only air and water temperature observations.

The SWAT-Ficklin et al. (2012) model had the highest spatial resolution, followed by VIC-RBM. As the Mohseni et al. (1998) model is zero-dimensional it doesn't have a spatial resolution, only yielding output on a per-location basis (the exact point where it is implemented).

The temporal resolutions of the models vary with the VIC-RBM and SWAT-Ficklin et al. (2012) models providing daily mean water temperatures and the Mohseni et al. (1998) model providing weekly mean water temperatures, with the capability of generating daily mean water temperatures in certain locations. The required temporal resolution for decision making varies according to the specific resource management concern and/or aquatic species.

From a "user friendliness" perspective, the Mohseni et al. (1998) model is the simplest to use, only requiring the use of simple statistical computing software. The calibration was quite straightforward and nearly instantaneous using the SCE method within an R program. The user-interface of the SWAT-Ficklin et al. (2012) model in addition to a well-developed support website lends to its ranking as second of the three models in "user friendliness." The calibration process can be expedited through additional SWAT-specific software such as SWAT-CUP (Calibration and Uncertainty Programs) used with parallel computing technology. The VIC-RBM model requires linux and the development of multiple input files, lending to its rating as the least "user friendly" of the three models being compared. All of this information is synthesized in Table 13.

Table 13: Model Comparison

Model	Data Inputs	Spatial Resolution	Temporal Resolution	User Friendliness
VIC-RBM	High	Medium	Daily Mean	3
SWAT-Ficklin	Medium	High	Daily Mean	2
Mohseni	Low	0 Dimensional	Weekly and/or Daily Mean	1

4.2 Climate Change Analysis

To analyze the results of the climate change analyses across the three different models, results from the climate change model runs were compared to the original modeled scenario (which is represented by the 100% precipitation rate 0° C air temperature increase scenario). The changes in water temperature versus the originally modeled water temperatures were assessed to predict warming rates due to air temperature changes and precipitation rate changes, as well as compare model effectiveness. Table 14 presents the changes (in degrees Celsius) in mean water temperature over the period of record; Table 15 presents this information as changes in mean seasonal water temperature.

Table 14: Mean Change in Water Temperature for Period of Record vs. Original Modeled Scenario

			Temperature Increase							
			0° C	1° C	2° C	3° C	4° C	5° C	6° C	7° C
Precipitation Rate	90%	Mohseni	0.00	0.46	0.92	1.38	1.85	2.31	2.78	3.25
		SWAT-Ficklin	0.09	0.72	1.37	2.09	2.81	3.56	4.22	5.12
		VIC-RBM	0.00	0.48	0.98	1.51	2.06	2.62	3.19	3.80
	100%	Mohseni	0.00	0.46	0.92	1.38	1.85	2.31	2.78	3.25
		SWAT-Ficklin	0.00	0.62	1.27	1.99	2.70	3.43	4.09	4.90
		VIC-RBM	0.00	0.47	0.97	1.50	2.04	2.59	3.17	3.78
	110%	Mohseni	0.00	0.46	0.92	1.38	1.85	2.31	2.78	3.25
		SWAT-Ficklin	-0.09	0.52	1.19	1.89	2.58	3.30	3.95	4.73
		VIC-RBM	0.00	0.46	0.96	1.48	2.02	2.57	3.13	3.73
	120%	Mohseni	0.00	0.46	0.92	1.38	1.85	2.31	2.78	3.25
		SWAT-Ficklin	-0.16	0.43	1.09	1.79	2.47	3.16	3.80	4.59
		VIC-RBM	0.00	0.46	0.95	1.46	1.99	2.54	3.10	3.70
	130%	Mohseni	0.00	0.46	0.92	1.38	1.85	2.31	2.78	3.25
		SWAT-Ficklin	-0.22	0.36	1.02	1.70	2.38	3.07	3.69	4.45
		VIC-RBM	0.00	0.45	0.93	1.44	1.97	2.51	3.06	3.65

Table 15: Mean Seasonal Changes in Temperature vs. Original Modeled Scenario

Precipitation Rate			Temperature Increase							
			0° C	1° C	2° C	3° C	4° C	5° C	6° C	7° C
Precipitation Rate	90%	Winter(DJF) Mohesni	0.00	0.22	0.47	0.77	1.11	1.50	1.94	2.44
		Spring(MAM) Mohseni	0.00	0.57	1.16	1.78	2.41	3.05	3.70	4.35
		Summer(JJA) Mohseni	0.00	0.40	0.75	1.04	1.29	1.50	1.68	1.82
		Fall(SON) Mohseni	0.00	0.65	1.30	1.93	2.56	3.16	3.75	4.30
		Winter(DJF) Ficklin	-0.03	0.40	0.77	1.27	1.72	2.23	2.70	3.41
		Spring(MAM) Ficklin	0.09	0.81	1.63	2.40	3.17	3.84	4.58	5.44
		Summer(JJA) Ficklin	0.36	1.27	2.34	3.40	4.28	5.13	6.00	6.87
		Fall(SON) Ficklin	0.18	0.91	1.66	2.54	3.47	4.57	5.25	6.40
		Winter(DJF) VIC-RBM	0.00	0.02	0.06	0.12	0.25	0.45	0.77	1.24
		Spring(MAM) VIC-RBM	0.02	0.80	1.58	2.33	3.04	3.73	4.46	5.27
		Summer(JJA) VIC-RBM	0.05	0.36	0.68	1.01	1.35	1.71	2.07	2.48
		Fall(SON) VIC-RBM	-0.06	0.76	1.64	2.60	3.59	4.55	5.41	6.18
	130%	Winter(DJF) Mohesni	0.00	0.22	0.47	0.77	1.11	1.50	1.94	2.44
		Spring(MAM) Mohseni	0.00	0.57	1.16	1.78	2.41	3.05	3.70	4.35
		Summer(JJA) Mohseni	0.00	0.40	0.75	1.04	1.29	1.50	1.68	1.82
		Fall(SON) Mohseni	0.00	0.65	1.30	1.93	2.56	3.16	3.75	4.30
		Winter(DJF) Ficklin	0.07	0.47	0.95	1.40	1.84	2.26	2.68	3.18
		Spring(MAM) Ficklin	-0.23	0.44	1.19	1.95	2.64	3.34	4.07	4.83
		Summer(JJA) Ficklin	-0.97	-0.14	0.76	1.77	2.81	3.75	4.69	5.77
		Fall(SON) Ficklin	-0.36	0.30	0.96	1.66	2.37	3.26	3.86	5.07
		Winter(DJF) VIC-RBM	0.00	0.01	0.05	0.11	0.23	0.43	0.74	1.21
		Spring(MAM) VIC-RBM	-0.04	0.74	1.53	2.30	3.01	3.70	4.42	5.22
		Summer(JJA) VIC-RBM	-0.14	0.07	0.29	0.53	0.79	1.07	1.37	1.68
		Fall(SON) VIC-RBM	0.15	0.95	1.83	2.79	3.78	4.74	5.60	6.36

4.2.1 Precipitation Changes

Analysis of the precipitation scenarios indicates that the changes in precipitation between 90% and 130% of observed are fairly negligible regarding changes in mean water temperatures for the period of record (7/21/2005– 4/15/2008). The differences in mean change in temperature for the period of record (versus the modeled 100% precipitation 0° C air temperature increase scenario) are presented in Table 16.

Table 16: Difference in Temperature Changes between 130% and 90% Precipitation Scenarios, per Temperature Increase Scenario

	Air Temperature Increase							
	0° C	1° C	2° C	3° C	4° C	5° C	6° C	7° C
Mohseni	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SWAT-Ficklin	-0.31	-0.36	-0.36	-0.39	-0.43	-0.49	-0.53	-0.66
VIC-RBM	0.00	-0.03	-0.05	-0.07	-0.09	-0.11	-0.12	-0.15

There are no changes due to precipitation in the Mohseni et al. (1998) model as these changes are not incorporated into the calculations for stream temperature. The Ficklin et al. (2012) model showed the greatest response to changes in precipitation, with the 90% precipitation scenario being the warmest and 130% being the coolest scenario and the changes becoming more exacerbated as the increase in air temperature became greater. The VIC-RBM model followed this same pattern, although to a lesser degree. This is consistent, as more precipitation means greater streamflows and thus more energy required to heat the greater volume of water. The precipitation scenarios (all for 0° C air temperature increase) for the Ficklin et al. (2012) model are plotted in Figure 24 and Figure 25 organized into “winter” months (October-March) and “summer” months (April-September).

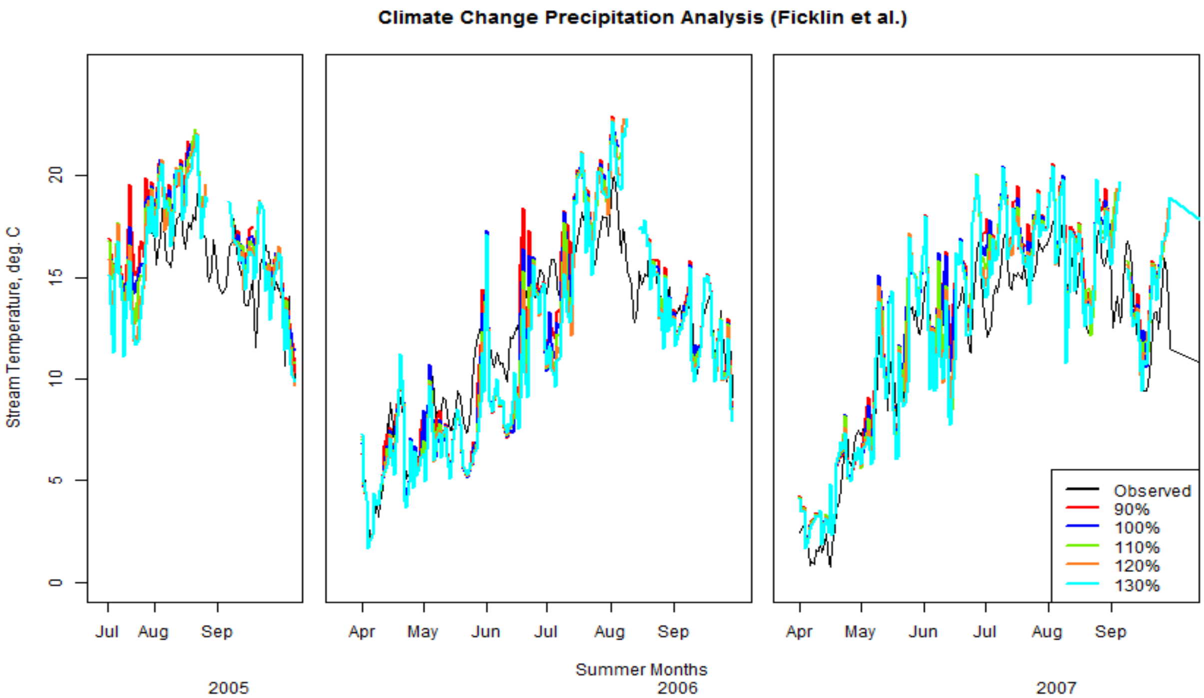

Figure 24: Projected Stream Temperatures in Summer by Precipitation Scenario

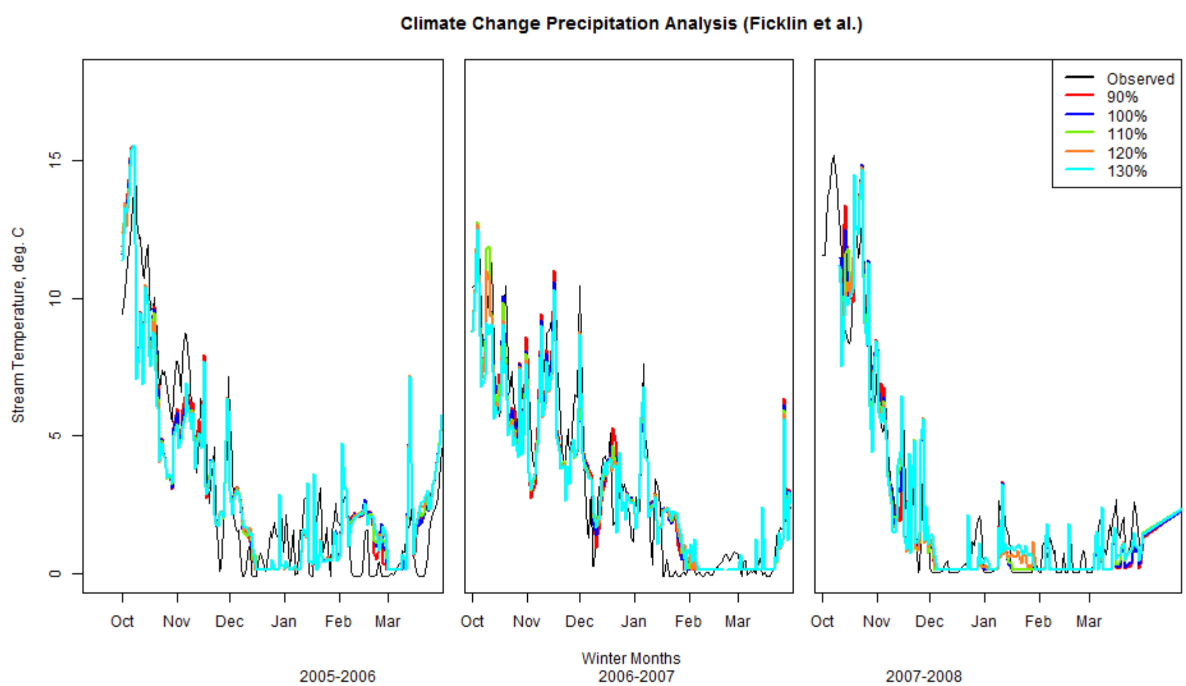

Figure 25: Projected Stream Temperatures in Winter by Precipitation Scenario

To examine mean changes in seasonal temperatures, the results are presented by season with the seasons defined as: Winter – December, January, and February; Spring – March, April, May; Summer – June, July, August; and Fall – September, October, and November (versus the modeled 100% precipitation 0° C air temperature increase scenario). A reduction in precipitation (90% of observed) resulted in slightly greater increases in seasonal temperatures. For example, the differences in mean changes in seasonal water temperatures for winter in the VIC-RBM model ranged from <0.01° C to 0.03° C between the 90% precipitation and 130% precipitation scenarios. A possible explanation for this is that water temperatures of smaller stream flows are more responsive to warming from solar radiation and ambient air temperatures (less thermal mass). Although not necessarily captured by the models, less winter precipitation (i.e. snow) results in less cold snow meltwater entering streams during winter and spring warming events – leading to warmer water temperatures.

The exceptions to these general findings were all fall temperature scenarios modeled by VIC-RBM and the winter T0-T5 scenarios for the Ficklin et al. (2012) model. Understanding that there are complex physical processes being modeled by VIC-RBM and SWAT-Ficklin et al. (2012) and that changes in precipitation can impact a number of related factors (snowpack, soil infiltration and saturation, groundwater levels, overland flow, subsurface flow), there are a few possible general explanations for these exceptions. The fall VIC-RBM scenarios for 90% precipitation may have smaller increases in temperature than the other precipitation scenarios because modeled stream temperatures shift dramatically in the VIC-RBM model in the fall months, and if there is reduced thermal mass of the body of water because of smaller streamflow, the shift may happen earlier and/or be more pronounced. The 90% precipitation scenarios run through the Ficklin model may be colder in the winter simply because the smaller streamflows, although slightly warmer in the other 3 seasons, have less thermal mass and are more responsive to winter air temperatures. This occurs until the reduced thermal mass is overpowered increases in stream temperature imposed by the 6° C and 7° C temperature increase scenarios.

4.2.2 Air Temperature Increases

Air temperature increases had a much greater impact on stream temperature than changes in precipitation as air temperature is the major driver of local stream temperature (Mohseni et al. 1998; Caissie et al. 2001; Morrill et al. 2005; Ficklin et al. 2012; Yearsly 2012). The difference in the mean change in water temperature for the period of record (7/21/2005– 4/15/2008) between the 7° C increase in air temperature and 0° C increase in air temperature decreased as the precipitation rate increased (Table 17). This can be attributed to lower streamflows having less thermal mass and therefore being more strongly impacted by air temperatures.

Table 17: Difference in Temperature Changes between 7° C and 0° C Temperature Increase Scenarios, per Precipitation Scenario

	Precipitation Rate				
	90%	100%	110%	120%	130%
Mohseni	3.25	3.25	3.25	3.25	3.25
SWAT-Ficklin	5.03	4.90	4.82	4.75	4.68
VIC-RBM	3.80	3.78	3.73	3.70	3.65

When analyzing the mean seasonal increases in stream temperature for the period of record, Fall had the largest predicted increase in stream temperatures (averaged across all three models). The largest increase for the VIC-RBM model was predicted for the Fall season, with the second largest increases for the Mohseni et al. (1998) and Ficklin et al. (2012) models also predicted in the Fall. For the VIC-RBM and Ficklin et al. (2012) models this is most likely due to streams gaining more thermal mass in the summer due to increased air temperatures and therefore maintaining higher water temperatures through the fall. Also, increased air temperatures in the fall could substantially reduce the number of snowfall events (with much more precipitation occurring as rain instead), meaning the precipitation itself is warmer and therefore not cooling streams.. Although the models are not accounting for this directly, it may be captured via hydrology (warmer air temperatures and smaller snow packs lead to earlier spring peaks of smaller magnitude). Both hydrology models incorporate snow pack into streamflow calculations. The spring season is the next most impacted, exhibiting the largest mean increase in water temperatures averaged across all three models. The Mohseni et al. (1998) model's predicted water temperature increases were the largest in the spring and fall, and the two were very close in magnitude. Similarly the VIC-RBM model's predicted water temperature increases were the largest in the spring and fall although they were not as close in magnitude as the Mohseni et al. (1998) model results. The Ficklin et al. (2012) model exhibited the largest increases in mean water temperature in the summer, closely followed by the fall.

4.2.3 Model Assessment

The VIC-RBM modeled climate change scenarios maintained fairly consistent patterns as air temperature changes increased. Across precipitation scenarios (from 90% to 130%), water temperatures began to approach a plateau around 20° C (Figure 26 and Figure 27) as summer highs decrease and spring and fall temperatures increase.

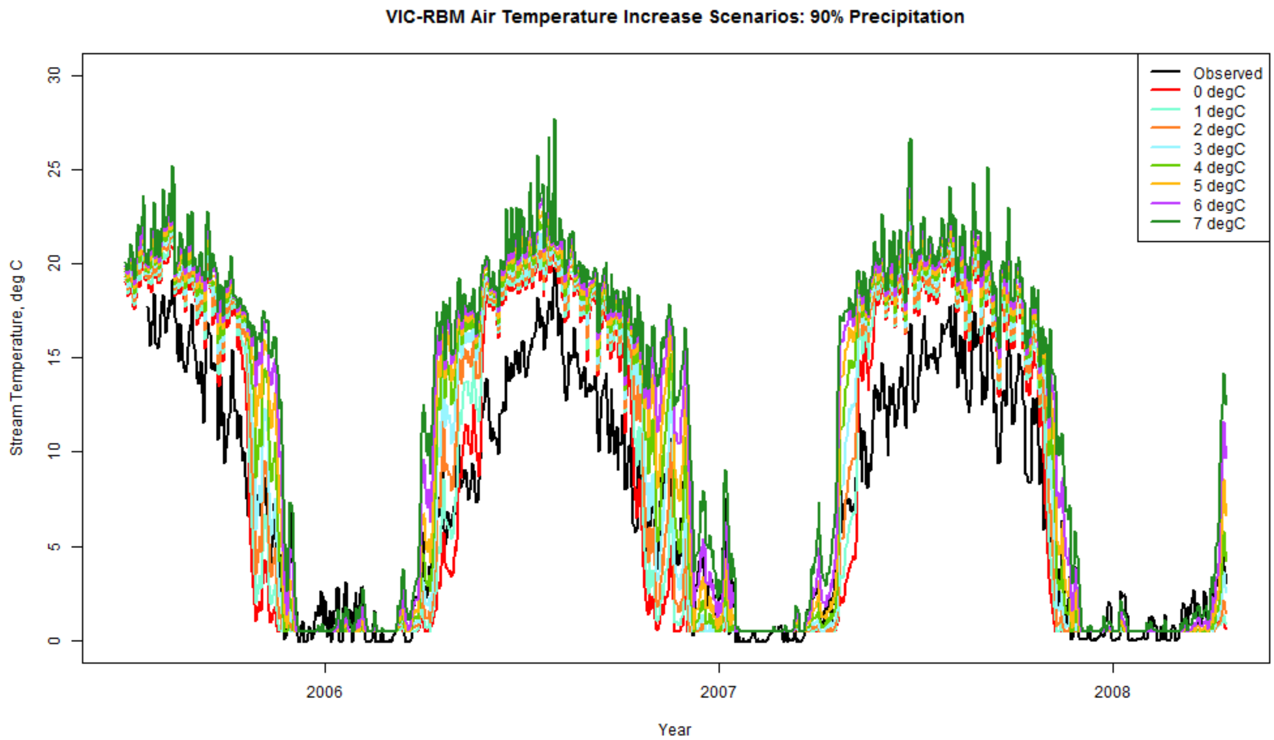

Figure 26: VIC-RBM Air Temperature Increase Scenarios: 90% Precipitation

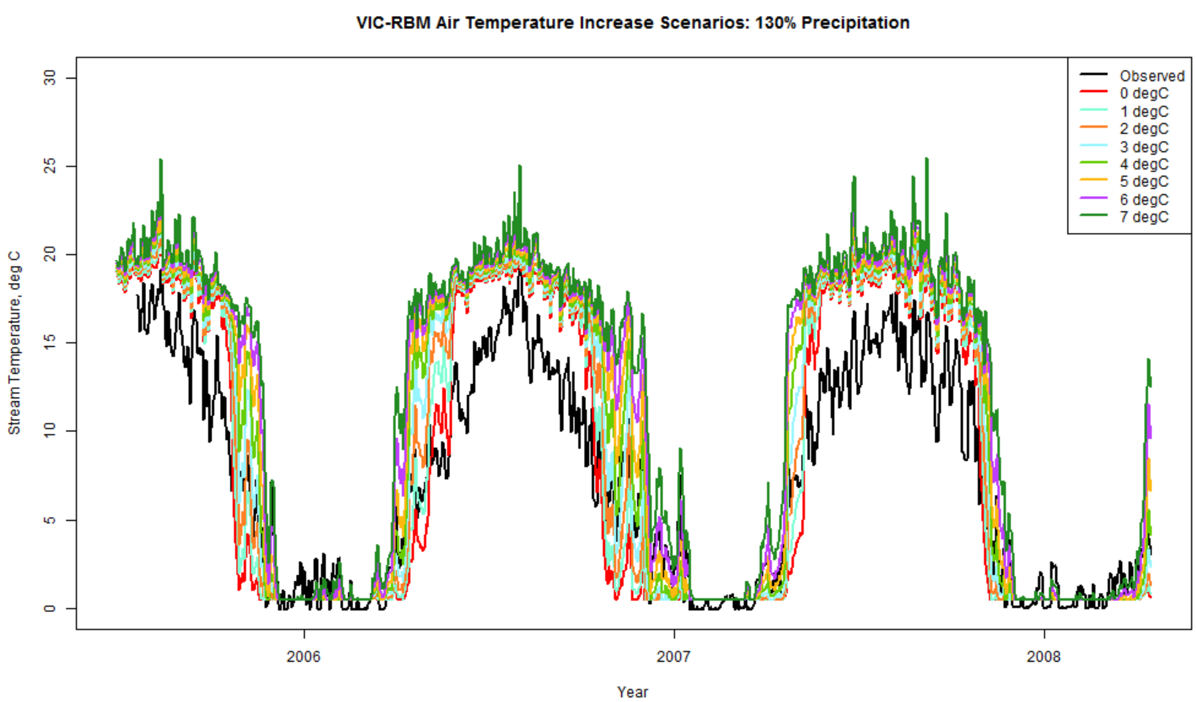

Figure 27: VIC-RBM Air Temperature Increase Scenarios: 130% Precipitation

The SWAT-Ficklin et al. (2012) climate change scenario predictions created a very similar pattern to the original modeled scenario (100% precipitation and 0° C air temperature increase). However, when air temperatures were increased by 7° C the modeled water temperatures appear to be unrealistically high. This indicates that the model is not capturing evaporative cooling effects (Figure 28).

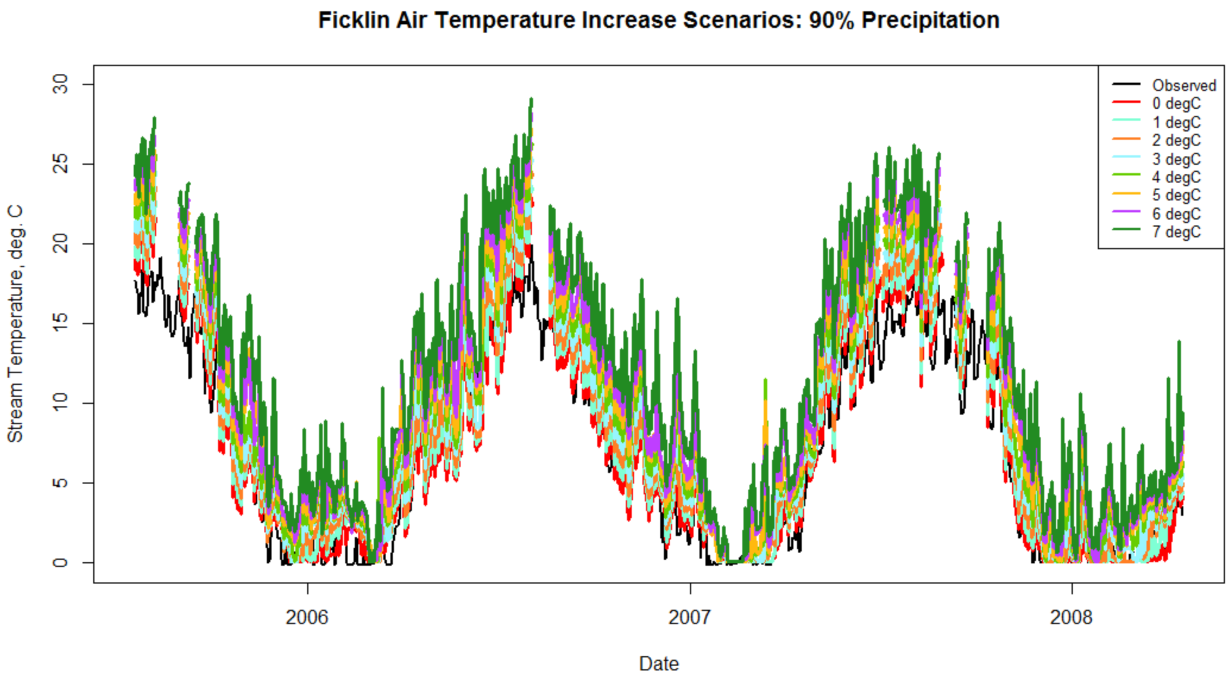

Figure 28: Ficklin Model Air Temperature Scenarios, 90% Precipitation Rate

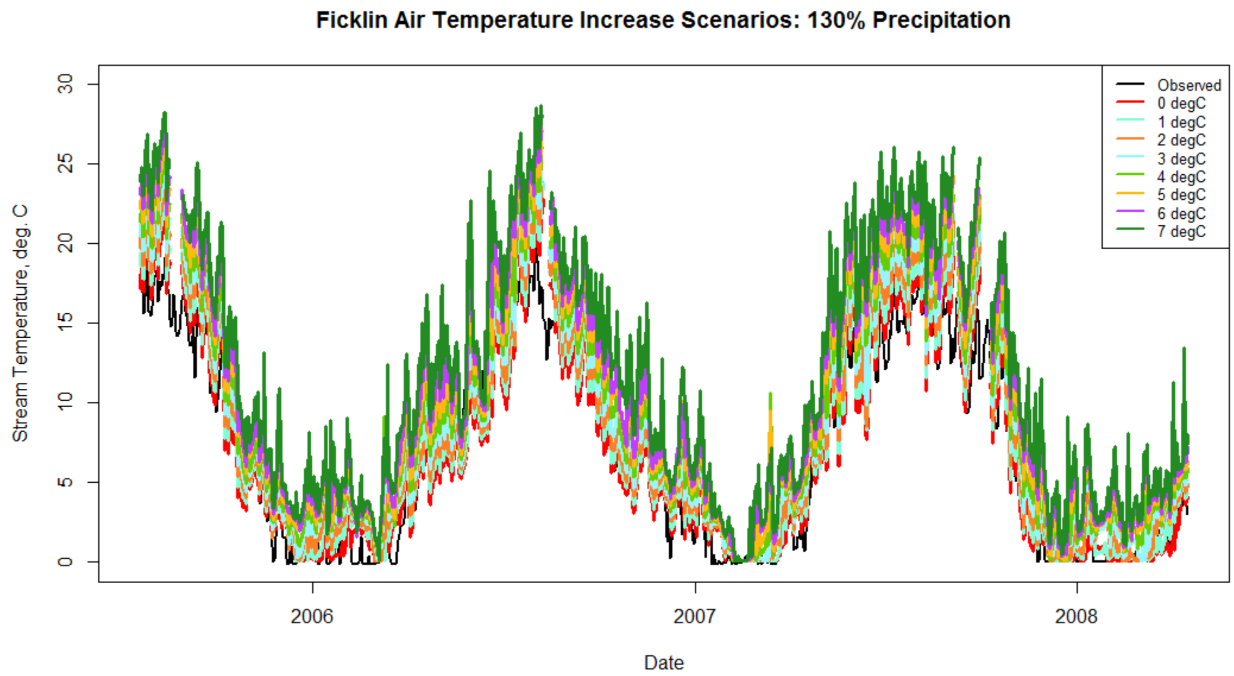

Figure 29: Ficklin Model Air Temperature Scenarios, 130% Precipitation Rate

The Mohseni et al. (1998) model fails to capture the highest observed temperatures in the Westfield basin, even for all of the climate change scenarios. That the model fails to meet the observed highs even in a scenario with a 7° C increase in air temperature is an indication of the failings of applying the model on a daily time-step. A component of the S-shaped curve regression is evaporative cooling at high water temperatures – the model as applied in the Westfield basin may be overestimating this evaporative cooling, and as the incremental increases in air temperature get higher, the projected high water temperatures begin to level-off around 17° C (Figure 30).

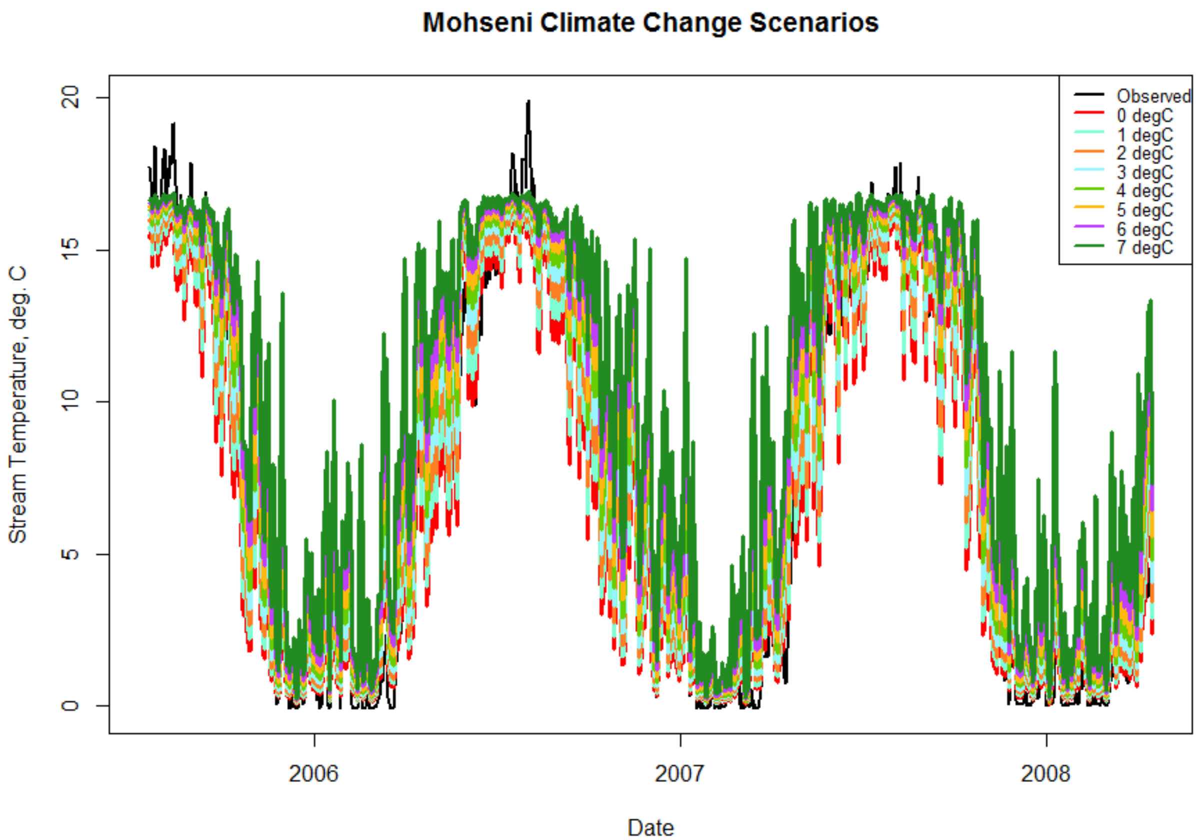

Figure 30: Mohseni Model Air Temperature Increase Scenarios

The projected water temperature increase per degree Celsius of air temperature increase was analyzed across all three models (Figure 31). The Mohseni et al. (1998) model yielded the most conservative result of 0.46 ° C of water warming per 1 ° C of air temperature increase. VIC-RBM predicts 0.54 ° C of water temperature increase and SWAT-Ficklin predicts 0.7 ° C of water warming per 1° C air temperature increase. These results are consistent with the findings of Morrill et al. (2005) who observed an increase of 0.6-0.8° C per 1° C air temperature increase using various statistical models across geographically diverse streams worldwide.

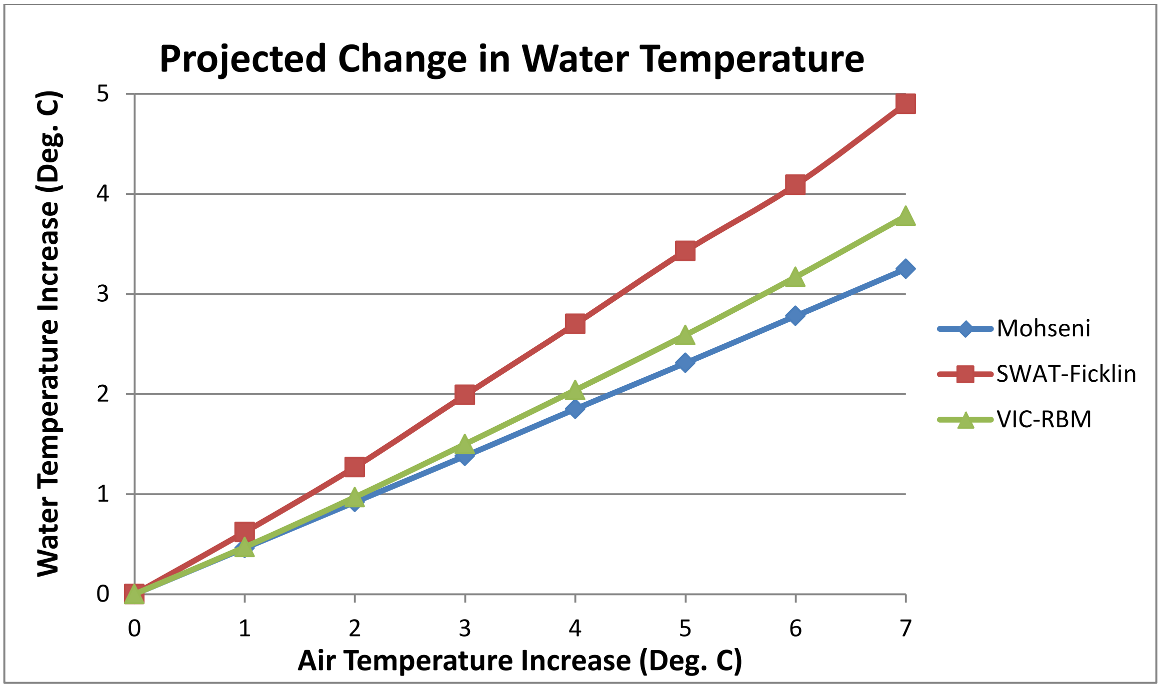

Figure 31: Projected Water Temperature Increase per Air Temperature Increase

4.3 Manager Needs

The survey results indicate that fine spatial resolution is important for resource managers, as many are primarily concerned with headwaters or tributaries (~71%). Examining the spatial resolution of the three models, the SWAT-Ficklin et al. (2012) model is the only model capable of meeting the needs of ~94% of those surveyed (spatial resolution of 5km-25km). Examining temporal resolution, none of the models selected are meeting the desired resolution of ~48% of those surveyed, who desire hourly stream temperature predictions. However, all three models provide mean temperatures, which were desired by the majority of responders. As the models provide the same temporal resolution and statistical output, spatial resolution is the deciding factor of whether a model meets their needs. A flow-chart of model selection is presented in Figure 32.

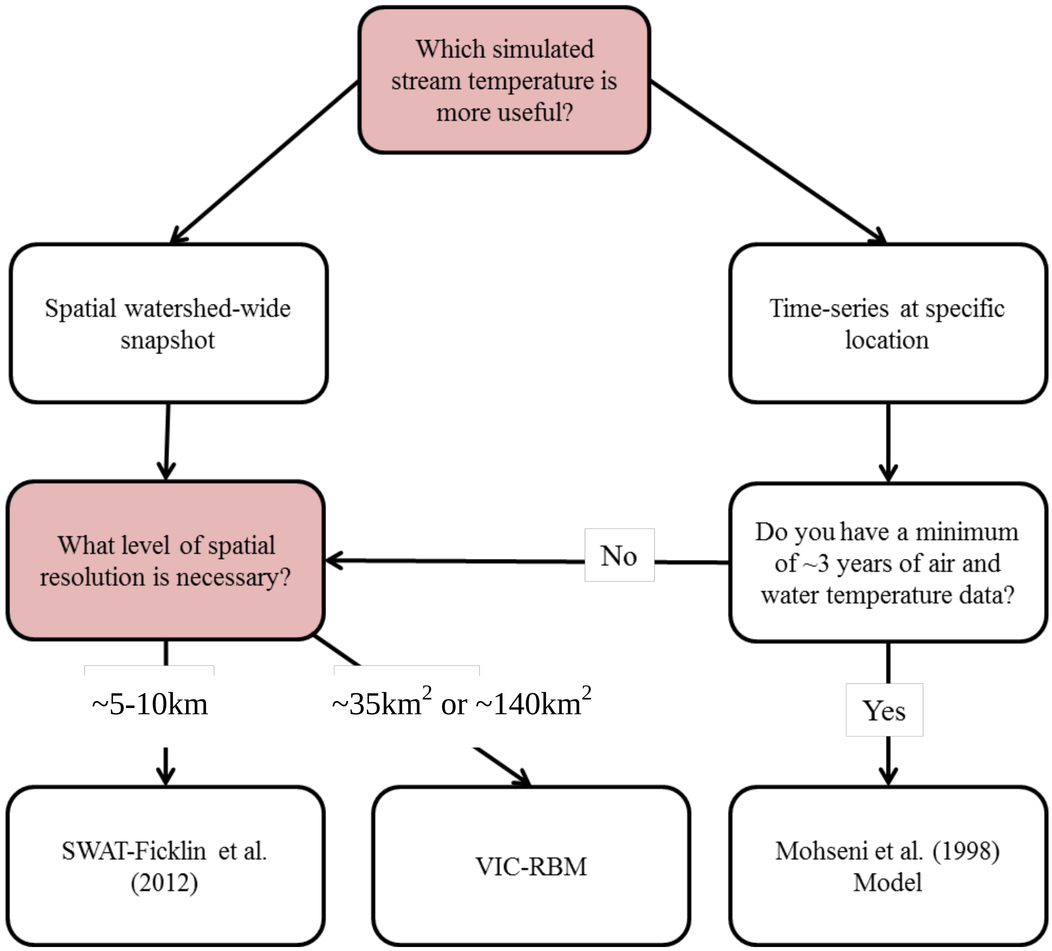

Figure 32: Flow Chart of Model Selection

4.4 Final Ranking

Under final ranking, relative weights were developed and applied to each metric to clearly articulate useful models for resource managers. These weights were informed by the results of the manager needs survey. For this quantitative ranking, the models were given an ordinal ranking of 1-3 for each metric, 1 being the best model in that category and 3 being the poorest performing model. Spatial resolution was identified as a very important and limiting factor, so it was assigned a weight of 0.3. Because all of the models met the desired temporal resolution, it was not included in the final ranking. Data input requirements are not very limiting, as a vast majority of the data required for these models is publicly available, therefore it was given a weight of 0.1. It is important to note that data input requirements excludes the water (and air) temperature observations necessary to calibrate and validate the models, instead it is referring solely to the additional data sets required for model operation (e.g. gridded meteorological forcings). Weights were split evenly with 0.15 each for NSE (represented by 1-NSE, as in this ranking a low score indicates better model performance) and RSR. User friendliness was assigned a weight of 0.3. Table 18 presents the model rankings within each metric and final weighted scores. In this final ranking, SWAT-Ficklin et al. (2012) received the best score, indicating that it is the most suited model of the three for resource managers to implement.

Table 18: Weighted Final Model Ranking

Model	Data Inputs	Spatial Resolution	Skill		User Friendliness	SCORE
			1-NSE	RSR		
VIC-RBM	3	2	0.279	0.528	3	1.92105
SWAT-Ficklin	2	1	0.082	0.286	2	1.1552
Mohseni	1	3	0.054	0.233	1	1.34305
Weight:	0.1	0.3	0.15	0.15	0.3	

5. Conclusions and Future Work

For resource managers selecting a stream temperature model to inform their management decsisions, there are three essential questions: 1) What data are available to calibrate and verify the model, 2) Are you most interested in generating a time series of temperatures or obtaining a spatially distributed, watershed-wide snapshot?, and 3) Is a climate change analysis to be performed?

If a time-series at a specific location is desired, then the Mohseni et al. (1998) model is an excellent option, if at least three years of paired air and water temperatures are available to inform the regression. If not, the SWAT-Ficklin et al. (2012) model is an appropriate choice, as it has higher spatial resolution than VIC-RBM. If a climate change analysis is to be performed, the Mohseni et al. (1998) model is not an ideal candidate – particularly if daily mean or maximum summer temperatures are of specific interest to resource managers. The Mohseni et al. (1998) model does not accurately capture those diurnal variations due to forced evaporative cooling (which may be less of an issue if implemented in basins in hotter regions where the effects of evaporative cooling are more pronounced). Additionally, the Mohseni et al. (1998) model does not incorporate streamflow changes (propagating from changes in climate).

If a spatial watershed-wide snapshot is of interest, VIC-RBM and SWAT-Ficklin et al. (2012) are most appropriate. If the study requires a continental-scale perspective, VIC-RBM is the more suitable model, whereas SWAT-Ficklin et al. (2012) provides greater spatial resolution for more localized resource management. Although the two have fairly similar data input-requirements, the SWAT-Ficklin et al. (2012) models have a more "user-friendly" interface through an ArcGIS platform – which is particularly good for working with stakeholders and visually presenting data and results. For climate change analysis, both pairs of models are able to accept future climate projections and incorporate them into predictions for both hydrology and water temperature.

For the specific basins studied, the results indicate that changes in air temperature directly influence stream temperature. There changes are a function of the change in air temperature, and are modulated by other factors such as the flow in the stream, the relative input of surface water and groundwater, and season (time of year). Although perhaps not appropriate for all streams, in this study changes in air temperature impact stream temperature most significantly during fall and spring. A 1 ° C change in air temperature results in a 0.46 ° C, 0.54 ° C, or 0.7 ° C increase in water temperature for the Mohseni et al. (1998), VIC-RBM, and SWAT-Ficklin et al. (2012) models respectively (Figure 31).

Precipitation has a lesser impact on stream temperature for the ranges studies (90% to 130% of observed), with changes in water temperature varying by 0 ° C to -0.66 ° C according to the specific model and air temperature increase (Table 16). Increased precipitation rates lead to slightly lower water temperatures, with the thermal buffer provided by increased flow rates becoming more pronounced as air temperature increases. For the SWAT-Ficklin model, precipitation increases from 90% to 130% lowered water temperature by an average of 0.44 ° C. For VIC-RBM, water temperatures were lowered by an average of 0.08 ° C. It is important to note that these results apply to the Westfield and Milwaukee basins where the models were applied, and were chosen as they are typical of basins in the Northeast; however, other types of streams may not exhibit the same relationships between precipitation, air temperature, and water temperature. For example, streams in the Driftless Area of Wisconsin demonstrate a significantly weaker relationship between air and water temperatures as they are highly impacted by groundwater. Research on water temperatures of Driftless Area streams is being done by NECSC-funded researchers at the University of Wisconsin Madison.

Future work includes completing the VIC-RBM model of the Milwaukee, assessing a broader suite of models, and tailoring existing models to meet the needs of resource managers more fully. Additional stream temperature models to consider beyond the ones outlined in this work, notably including Isaak et al.'s (2010) spatial statistical stream temperature model (which was not assessed in this research because of the prohibitively high stream temperature observations requirements) and the pairing of Yearsley's (2009; 2012) RBM model with a different hydrology model, the Distributed Hydrology Soil Vegetation Model (DHSVM) (Wigmosta and Burges 1997). The application of these findings to many streams and regression analysis of season changes in steam temperature due to air temperature changes could provide very useful and pertinent information to aquatic resource managers in the Northeast Climate Science Center region and beyond.

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Appendix A: Westfield Basin Model Parameters

A1 Westfield SWAT Parameters

File	Parameter	Calibrated Value	Units
Basin	SFTMP	-1	deg C
	SMTMP	0.5	deg C
	SMFMX	4	mm/C-day
	SMFMN	4	mm/C-day
	TIMP	0.03	
	SNOCOVMX	180	mm
	SNO50COV	0.2	
	ESCO	0.75	
	EPCO	1	
	SURLAG	0.1	
Groundwater	GW_DELAY	10	days
	ALPHA_BF	0.2	days
	GW_QMIN	100	mm
	GW_REVAP	0.2	
	REVAPMN	0	mm
	RCHRG_DP	0	fraction
HRU	SLSUBBSN	56	m
	HRU_SLP	0.45	m/m
Routing	CH_K2	40	mm/hr
Soils	SOL_AWC	0.09	mm/mm

A2 Westfield Ficklin et al. (2012) Parameters

Date From	Date To	Alpha	Beta	Phi	K	Lag
1	65	1.0	1.0	0.80	0.100	5
66	125	1.0	1.0	0.75	0.050	14
126	285	1.0	1.0	0.75	0.050	14
286	366	1.0	1.0	0.80	0.150	7

A3 Westfield Mohseni et al. (1998) Parameters

Parameter	Calibrated Value
Alpha	16.99335
Beta	12.12728
Theta	0.7524177
Mu	5.601222E-06

Appendix B: Milwaukee Basin Model Parameters

B1 Milwaukee SWAT Parameters

File	Parameter	Calibrated Value	Units
Basin	SFTMP	1.0	deg C
	SMTMP	0.0	deg C
	SMFMX	4.2	mm/C-day
	SMFMN	2.3	mm/C-day
	TIMP	0.007	
	SNOCOVMX	200	mm
	SNO50COV	0.5	
	ESCO	0.77	
	EPCO	0.67	
	SURLAG	0.05	
Groundwater	GW_DELAY	187	days
	ALPHA_BF	0.27	days
	GW_QMIN	700	mm
	GW_REVAP	0.035	
	REVAPMN	300	mm
	RCHRG_DP	0.56	fraction
HRU	SLSUBBSN	95	m
	HRU_SLP	0.13	m/m

B2 Milwaukee Ficklin et al. (2012) Parameters

Date From	Date To	Alpha	Beta	Phi	K	Lag
1	120	1.0	1.0	1.00	0.050	7
121	325	1.0	1.0	1.00	0.015	7
326	366	1.0	1.0	1.00	0.050	7

B3 Milwaukee Mohseni et al. (1998) Parameters

Parameter	Calibrated Value
Alpha	24.75905
Beta	12.10435
Theta	0.8456428
Mu	0.05000733

Appendix C: Changes in Seasonal Mean Water Temperature for Climate Change Scenarios vs. Original Modeled Scenario

	P90T0	P90T1	P90T2	P90T3	P90T4	P90T5	P90T6	P90T7	P100T0	P100T1	P100T2	P100T3	P100T4	P100T5	P100T6	P100T7
Winter(DJF)_MOHSENI	0.00	0.22	0.47	0.77	1.11	1.50	1.94	2.44	0.00	0.22	0.47	0.77	1.11	1.50	1.94	2.44
Spring(MAM)_MOHSENI	0.00	0.57	1.16	1.78	2.41	3.05	3.70	4.35	0.00	0.57	1.16	1.78	2.41	3.05	3.70	4.35
Summer(JJA)_MOHSENI	0.00	0.40	0.75	1.04	1.29	1.50	1.68	1.82	0.00	0.40	0.75	1.04	1.29	1.50	1.68	1.82
Fall(SON)_MOHSENI	0.00	0.65	1.30	1.93	2.56	3.16	3.75	4.30	0.00	0.65	1.30	1.93	2.56	3.16	3.75	4.30
Winter(DJF)_FICKLIN	-0.03	0.40	0.77	1.27	1.72	2.23	2.70	3.41	0.00	0.40	0.82	1.35	1.81	2.28	2.75	3.31
Spring(MAM)_FICKLIN	0.09	0.81	1.63	2.40	3.17	3.84	4.58	5.44	0.00	0.71	1.47	2.27	3.03	3.75	4.46	5.20
Summer(JJA)_FICKLIN	0.36	1.27	2.34	3.40	4.28	5.13	6.00	6.87	0.00	0.87	1.82	2.96	4.01	4.92	5.77	6.64
Fall(SON)_FICKLIN	0.18	0.91	1.66	2.54	3.47	4.57	5.25	6.40	0.00	0.74	1.49	2.25	3.03	4.06	4.79	6.09
Winter(DJF)_VICRBM	0.00	0.02	0.06	0.12	0.25	0.45	0.77	1.24	0.00	0.02	0.05	0.12	0.24	0.45	0.76	1.23
Spring(MAM)_VICRBM	0.02	0.80	1.58	2.33	3.04	3.73	4.46	5.27	0.00	0.78	1.57	2.32	3.03	3.72	4.45	5.26
Summer(JJA)_VICRBM	0.05	0.36	0.68	1.01	1.35	1.71	2.07	2.48	0.00	0.29	0.58	0.89	1.22	1.55	1.93	2.29
Fall(SON)_VICRBM	-0.06	0.76	1.64	2.60	3.59	4.55	5.41	6.18	0.00	0.81	1.69	2.66	3.65	4.61	5.48	6.25

	P110T0	P110T1	P110T2	P110T3	P110T4	P110T5	P110T6	P110T7	P120T0	P120T1	P120T2	P120T3	P120T4	P120T5	P120T6	P120T7
Winter(DJF)_MOHSENI	0.00	0.22	0.47	0.77	1.11	1.50	1.94	2.44	0.00	0.22	0.47	0.77	1.11	1.50	1.94	2.44
Spring(MAM)_MOHSENI	0.00	0.57	1.16	1.78	2.41	3.05	3.70	4.35	0.00	0.57	1.16	1.78	2.41	3.05	3.70	4.35
Summer(JJA)_MOHSENI	0.00	0.40	0.75	1.04	1.29	1.50	1.68	1.82	0.00	0.40	0.75	1.04	1.29	1.50	1.68	1.82
Fall(SON)_MOHSENI	0.00	0.65	1.30	1.93	2.56	3.16	3.75	4.30	0.00	0.65	1.30	1.93	2.56	3.16	3.75	4.30
Winter(DJF)_FICKLIN	0.01	0.42	0.88	1.36	1.82	2.27	2.70	3.26	0.05	0.45	0.90	1.38	1.82	2.25	2.68	3.23
Spring(MAM)_FICKLIN	-0.09	0.62	1.37	2.13	2.89	3.63	4.35	5.08	-0.16	0.53	1.27	2.02	2.74	3.48	4.22	4.95
Summer(JJA)_FICKLIN	-0.43	0.45	1.47	2.48	3.55	4.55	5.51	6.42	-0.73	0.11	1.07	2.17	3.10	4.11	5.10	6.12
Fall(SON)_FICKLIN	-0.12	0.56	1.27	2.04	2.81	3.72	4.32	5.73	-0.26	0.41	1.08	1.80	2.57	3.49	4.09	5.29
Winter(DJF)_VICRBM	0.00	0.02	0.05	0.12	0.24	0.44	0.75	1.22	0.00	0.02	0.05	0.11	0.23	0.44	0.75	1.22
Spring(MAM)_VICRBM	-0.01	0.76	1.56	2.31	3.02	3.72	4.44	5.24	-0.03	0.75	1.55	2.30	3.02	3.71	4.43	5.23
Summer(JJA)_VICRBM	-0.05	0.21	0.48	0.77	1.07	1.40	1.73	2.08	-0.10	0.14	0.38	0.65	0.93	1.23	1.55	1.89
Fall(SON)_VICRBM	0.06	0.87	1.75	2.71	3.71	4.66	5.53	6.29	0.10	0.91	1.79	2.76	3.75	4.70	5.57	6.33

	P130T0	P130T1	P130T2	P130T3	P130T4	P130T5	P130T6	P130T7
Winter(DJF)_MOHSENI	0.00	0.22	0.47	0.77	1.11	1.50	1.94	2.44
Spring(MAM)_MOHSENI	0.00	0.57	1.16	1.78	2.41	3.05	3.70	4.35
Summer(JJA)_MOHSENI	0.00	0.40	0.75	1.04	1.29	1.50	1.68	1.82
Fall(SON)_MOHSENI	0.00	0.65	1.30	1.93	2.56	3.16	3.75	4.30
Winter(DJF)_FICKLIN	0.07	0.47	0.95	1.40	1.84	2.26	2.68	3.18
Spring(MAM)_FICKLIN	-0.23	0.44	1.19	1.95	2.64	3.34	4.07	4.83
Summer(JJA)_FICKLIN	-0.97	-0.14	0.76	1.77	2.81	3.75	4.69	5.77
Fall(SON)_FICKLIN	-0.36	0.30	0.96	1.66	2.37	3.26	3.86	5.07
Winter(DJF)_VICRBM	0.00	0.01	0.05	0.11	0.23	0.43	0.74	1.21
Spring(MAM)_VICRBM	-0.04	0.74	1.53	2.30	3.01	3.70	4.42	5.22
Summer(JJA)_VICRBM	-0.14	0.07	0.29	0.53	0.79	1.07	1.37	1.68
Fall(SON)_VICRBM	0.15	0.95	1.83	2.79	3.78	4.74	5.60	6.36