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Chapter 3

Watershed-Scale Hydrological Modeling Methods and Applications

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/53596

1. Introduction

Pollution of surface water with harmful chemicals and eutrophication of rivers and lakes with excess nutrients are serious environmental concerns. The U.S. Environmental Protection Agency (USEPA) estimated that 53% of the 27% assessed rivers and streams miles and 69% of the 45% assessed lakes, ponds, and reservoirs acreage in the nation are impaired (USEPA, 2010). In Mississippi, 57% of the 5% assessed rivers and streams miles are impaired (USEPA, 2010). These impairment estimates may increase when assessments of more water bodies are performed and water quality criteria are improved. The most common water pollution concerns in U.S. rivers and streams are sediment, nutrients (Phosphorus and Nitrogen) and pathogens. Hydrological processes can significantly impact on the transport of water quality pollutants.

Non-point source pollution from agricultural, forest, and urban lands can contribute to water quality degradation. Total Maximum Daily Loads (TMDLs) are developed by states to improve water quality. The TMDL requires identifying and quantifying pollutant contributions from each source to devise source-specific pollutant reduction strategies to meet applicable water quality standards. Commonly, water quality assessment at the watershed scale is accomplished using two techniques: (a) watershed monitoring and (b) watershed modeling. Watershed models provide a tool for linking pollutants to the receiving streams. Models provide quick and cost-effective assessment of water quality conditions, as they can simulate hydrologic processes, which are affected by several factors including climate change, soils, and agricultural management practices. However, methods used to develop a model for watersheds can significantly impact in the model outputs. Here several hydrological and water quality models are described. Case studies of two commonly used models with calibration and validation are provided with current and future climate change scenarios. This

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book chapter briefly reviews currently available hydrologic and water quality models, and presents model application case studies, to provide a foundation for further model development and watershed assessment studies.

2. Review of water quality models

Several useful hydrologic and water quality models are available today, each with diverse capabilities for watershed assessment. Many of these models are relevant to water quality goal assessment and implementation. Modeling of hydrology, sediment and nutrients has developed substantially, but advances have not always been consistent with the needs of the water quality goals program. Comprehensive education and training with model applications and case studies are needed for users to understand the potentials, limitations, and suitable applications of a model. Review of several hydrological models (e.g. SWAT, AnnAGNPS, HSPF, SPARROW, GLEAMS, WEPP, EFDC etc.) including models description and application within the U.S. or other countries are discussed.

2.1. SWAT model

The SWAT model is developed and supported by the USDA/ARS. It is a physically based watershed-scale continuous time-scale model, which operates on a daily time step. The SWAT model can simulate runoff, sediment, nutrients, pesticide, and bacteria transport from agricultural watersheds (Arnold et al., 1998). The SWAT model delineates a watershed, and sub-divides that watershed in to sub-basins. In each sub-basin, the model creates several hydrologic response units (HRUs) based on specific land cover, soil, and topographic conditions. Model simulations that are performed at the HRU levels are summarized for the sub-basins. Water is routed from HRUs to associated reaches in the SWAT model. SWAT first deposits estimated pollutants within the stream channel system then transport them to the outlet of the watershed. The HRUs provide opportunity to include processes for possible spatial and temporal variations in model input parameters. The hydrologic module of the model quantifies a soil water balance at each time step during the simulation period based on daily precipitation inputs.

The SWAT model distinguishes the effects of weather, surface runoff, evapo-transpiration, crop growth, nutrient loading, water routing, and the long-term effects of varying agricultural management practices (Neitsch et al., 2005). In the hydrologic module of the model, the surface runoff is estimated separately for each sub-basin and routed to quantify the total surface runoff for the watershed. Runoff volume is commonly estimated from daily rainfall using modified SCS-CN method. The Modified Universal Soil Loss Equation (MUSLE) is used to predict sediment yield from the watershed. The SWAT model has been extensively applied for simulating stream flow, sediment yield, and nutrient modeling (Gosain et al., 2005; Vache et al., 2002; Varanou et al., 2002). The model needs several data inputs to represent watershed conditions which include: digital elevation model (DEM), land use land cover, soils, climate data. The SWAT model is an advancement of the Simulator for Water

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Resources in Rural Basins (SWRRB) and Routing Outputs to Outlet (ROTO) models. The SWAT model development was influenced by other models like CREAMS (Knisel, 1980), GLEAMS (Leonard et al., 1987), and EPIC (Williams et al., 1984; Neitsch et al., 2002).

The SWAT model has been recently applied to assess watershed conditions of the U.S. (Gassman et al., 2007; Parajuli et al., 2008; 2009; Parajuli 2010a; 2011; 2012; Chaubey et al., 2010) and internationally such as Ethiopia (Betrie et al., 2011); Kenya and northwest Tanzania (Dessu and Melesse, 2012); Bulgaria and Greece (Boskidis et al., 2012); and Australia (Githui et al., 2012).

2.2. AnnAGNPS

The AnnAGNPS model is a product of the USDA Agriculture Research Service (USDA-ARS) and the USDA Natural Resources Conservation Service (USDA-NRCS) to evaluate non-point source pollution from agriculture watersheds. Similar to the SWAT model, it is a physically based continuous and daily time step model used to simulate surface runoff, sediment, and nutrient yields (Cronshey and Theurer, 1998; Bingner and Theurer, 2003). The AnnAGNPS is considered an enhanced modification to the single event based Agricultural Non-Point Source (AGNPS) model (Young et al., 1989), as it retains many features of AGNPS (Yuan et al., 2001). Unlike AGNPS, the AnnAGNPS delineates watershed, sub-divides the watershed into small drainage areas with homogenous land use, soils, etc. The sub-areas are integrated and simulated surface runoff and pollutant loads through rivers and streams within the sub-areas and watershed, which is enhanced from the AGNPS.

The AnnAGNPS model utilizes and incorporates components or sub-components from several other models such as; Revised Universal Soil Loss Equation (RUSLE) model (Renard et al., 1997); Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model (Knisel, 1980); Groundwater Loading Effects on Agricultural Management Systems (GLEAMS) model (Leonard et al., 1987); and Erosion Productivity Impact Calculator (EPIC) Model (Sharpley and Williams, 1990). The AnnAGNPS model represents small watershed areas using a cell-based approach, with land and soil property characterization similar to SWAT model HRUs. Daily soil moisture contents are calculated using the Curve Number (CN) method, which help to quantify surface and subsurface flows. The AnnAGNPS model uses the RUSLE to estimate sediment yields.

Refereed AnnAGNPS model based evaluations have been applied predominantly to watersheds located in the U.S. (Yuan et al., 2011; 2002; Zuercher et al., 2011; Polyakov et al., 2007). However, the model also has been applied in other countries such as Mediterranian (Licciardello et al., 2011; 2007); Australia (Baginska et al., 2003), and China (Hua et al., 2012).

2.3. WEPP

The Water Erosion Prediction Project (WEPP) model is a product of USDA. The WEPP model is a process-based, distributed parameter, single storm and continuous based model used to predict surface flow and sediment yields from the hill slopes and small watersheds. WEPP allows simulation of the effects of crop, crop rotation, contour farm-

ing, and strip cropping. The WEPP model components includes weather generation, snow accumulation and melt, irrigation, infiltration, overland flow process, water balance, plant growth, residue management, soil disturbance by tillage, and erosion processes. The WEPP model considers sheet and rill erosion processes to predict erosion. The WEPP model incorporates modified water balance and percolation components from the SWRRB model (Williams and Nicks, 1985). The WEPP model utilizes and incorporates components or sub-components from several other models such as; EPIC (Williams et al., 1984); and CREAMS model (Knisel, 1980). The WEPP model has undergone continuous development since 1992 (1992-1995 with DOS version; 1997-2000 with window interface; 1999-2009 with Geo-WEPP ArcView/ArcGIS extensions; and 2001-present with web-browser interface; Flanagan et al., 2007; Foltz et al., 2011).

Refereed WEPP-model-based evaluations exist predominantly for agricultural fields or small watersheds located in the U.S. (Dun et al., 2010; Flanagan et al., 2007; Foltz et al., 2011). However, the WEPP has been applied in other countries such as China (Zhang et al., 2008).

2.4. GLEAMS

Groundwater Loading Effects of Agricultural Management Systems (GLEAMS) is a daily time-step, continuous, field-scale hydrological and pollutant transport mathematical model (Leonard et al., 1987). The GLEAMS model can simulate surface runoff, percolation, nutrient and pesticide leaching, erosion and sedimentation. The GLEAMS model requires several daily climate data including mean daily air temperature, daily rainfall, mean monthly maximum and minimum temperatures, wind speed, solar radiation and dew-point temperature data. The soil input parameters in the model can be obtained from the State Soil Geographic Database (STATSGO) or Soil Survey Geographic Database (SSURGO) soil data. Previous studies described the ability of GLEAMS model to predict nitrate transport process from the agricultural areas (Shirmohammadi et al., 1998; Bakhsh et al., 2000; Chinkuyu and Kanwar, 2001).

Refereed GLEAMS model applications have been published predominantly for field scale studies in the U.S. (Bakhsh et al., 2000; Chinkuyu et al., 2004). However, GLEAMS also has been applied in a few other countries, such as China (Zhang et al., 2008).

2.5. HSPF model

The hydrological simulation program—FORTRAN (HSPF) is a product of U.S. Environmental Protection Agency (US-EPA), which is a comprehensive model used for modeling processes related to water quantity and quality in watersheds of various sizes and complexities (Bicknell et al. 2001). It simulates both the land area of watersheds and the water bodies. The HSPF model uses input data including hourly history of rainfall, temperature and solar radiation; land surface characteristics/land use conditions; and land management practices to predict parameters at watershed scales. The results of model simulations are based on a time history of the quantity and quality of runoff from an urban, forest or agricultural watershed, which include surface runoff, sediment load, nutrients and pesticide concentrations. The

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HSPF model can simulate three sediment types (sand, silt, and clay) in addition to organic chemicals and alternative products. A detailed description of HSPF model can be found in Bicknell et al. (2001).

There have been hundreds of applications of HSPF around the world (Bicknell et al., 2001; Akter and Babel, 2012; Ouyang et al., 2012; Rolle et al., 2012). Examples include applications in a large watershed at the Chesapeake Bay, in a small watershed near Watkinsville, GA, with the experimental plots of a few hectares and in other areas such as Seattle, WA, Patuxent River, MD., and Truckee-Carson Basins, NV. Details are available at: (http://water.usgs.gov/cgi-bin/man_wrdapp?hspf).

2.6. SPARROW

The SPAtially-Referenced Regression On Watershed attributes (SPARROW) model is a watershed modeling tool for comparing water-quality data collected at a network of monitoring stations to characterize watersheds containing the stations (Smith et al., 1997; Schwarz et al., 2008). The SPARROW model has a nonlinear regression equation depicting the non-conservative transport of contaminants from the point and diffuse sources on land surfaces to streams and rivers. The SPARROW predicts contaminant flux, concentration, and yield in streams. It has been used to evaluate alternative hypotheses about important contaminant sources and watershed properties that control contaminant load and transport over large spatial scales. The SPARROW can be used to explain spatial patterns of stream water quality in relation to human activities and natural processes.

Numerous applications of SPARROW have been performed to assess water quality in watersheds in recent years. Brown (2011) investigated nutrient sources and transport in the Missouri River Basin with SPARROW. Saad et al. (2011) applied SPARROW to estimate nutrient load and to improve water quality monitoring design using a multi-agency dataset. Alam and Goodall (2012) examined the effects of hydrologic and nitrogen source changes on nitrogen yield in the contiguous United States with SPARROW.

2.7. EFDC

The Environmental Fluid Dynamics Code (EFDC) is a multifunctional surface water modeling system, which includes hydrodynamic, sediment-contaminant, and eutrophication components (Hamrick, 1996) and is available to the public through US-EPA website available at: http://www.epa.gov/ceampubl/swater/efdc/index.html. The EFDC can be used to simulate aquatic systems in multiple dimensions with the stretched or sigma vertical coordinates and the Cartesian (or curvilinear), and orthogonal horizontal coordinates to represent the physical characteristics of a water body. A dynamically-coupled transport process for turbulent kinetic energy, turbulent length scale, salinity and temperature are included in the EFDC model. The EFDC allows for drying and wetting in shallow water bodies by a mass conservation scheme.

Refereed EFDC-model-based evaluations exist predominately for stream ecosystems. Examples include a three-dimensional hydrodynamic model of the Chicago River, Illinois (Sinha

et al., 2012); the effect of interacting downstream branches on saltwater intrusion in the Modaomen Estuary, China (Gong et al., 2012); and comparison of two hydrodynamic models of Weeks Bay, Alabama (Alarcon et al., 2012).

2.8. SWMM

The US-EPA's Storm Water Management Model (SWMM) was initially developed in 1971, and has been significantly upgraded (http://www.epa.gov/nrmrl/wswrd/wq/models / swmm/index.htm). The SWMM model is a widely used model for planning, analysis and design related to storm water runoff, sewers, and other drainage systems in urban areas. SWMM can simulate single storm-events or provide continuous prediction of surface-runoff quantity and quality from urban areas. In addition to predicting surface-runoff quantity and quality, the model can also predict flow rate, flow depth, and water quality in each pipe and channel.

There have been numerous applications of SWMM in the literature recently. Blumensaat et al. (2012) investigated sewer transport with SWMM under minimum data requirements. Cantone and Schmidt (2011) applied SWMM to improve understanding of the hydrologic response of highly urbanized watershed catchments like the Illinois Urban areas. Talei and Chua (2012) estimated the influence of lag-time on storm event-based hydrologic impacts (e.g. rainfall, surface-runoff) using the SWMM model and a data-driven approach.

3. Methods to develop a model

Appropriate methods are needed to develop a model, utilize different data sources (e.g. digital elevation, soil, land use, weather etc.), and develop methods to quantify pollutants source loads in the model. As examples, the methods development process is described here for two commonly used models (i.e., SWAT and HSPF).

3.1. SWAT model

The SWAT model utilizes digital elevation model (DEM), soils, land cover, and weather data such as precipitation, temperature, wind speed, solar radiation, and relative humidity. SWAT delineates watershed boundary and topographic characteristics of the watershed using National Elevation Dataset called digital elevation model (DEM) data, which are available in the grid form with different resolutions (e.g. 30m x 30m grid; 10m x 10m grid) generally collected by U.S. Geological survey (USGS, 1999) or other sources. The 30m grid data are commonly used in the large scale watershed modeling work. However, small watershed or field scale modeling may benefit from using of 10m x 10m resolution DEM data. Model defines land use inputs in the model are described using distributed land cover data (USDA-NASS, 2010) or other land use data. The time-specific land-cover data (e.g. 1992, 2001 and 2006) for the U.S. and Puerto Rico can be downloaded from the National Land Cover Database (NLCD), a publicly available data source. The distributed land cover data with land use classifications can provide essential model input for the watershed assess-

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ment. Currently, land-use data layers are available in geographic information systems (GIS) format, which is applicable for the watershed modeling.

The SWAT model also requires distributed detail soils data, which is available from either State Soil Geographic (STATSGO) database or Soil Survey Geographic (SSURGO) databases (USDA, 2005). The SSURGO database is the most detailed data source currently available in the U.S. as it provides more soil polygons per unit area. The DEM, soils, and landuse geographic data layers should be all projected in one projection system (e.g. Universal Transverse Mercator-UTM 1983, zone 16).

Most of the watershed or field scale models (e.g. SWAT, WEPP) have embedded weather stations and climate generators. However, more field-specific climate inputs (e.g. rainfall; daily minimum, maximum and mean temperatures; solar radiation; relative humidity, and wind speed) can be allowed in the model for the watershed assessment. Weather data such as daily rainfall and ambient temperature can be downloaded from the National Climatic Data Center (NCDC, 2012). Other field-specific model input parameters such as irrigation (e.g. auto or manual irrigation), fertilizer application (application rates, fertilizer type), crop rotation (e.g. corn after soybean), tillage (e.g. conventional, reduced, no-tillage), planting and harvesting dates can be defined (Parajuli, 2010b).

3.2. HSPF model

The major procedures in water quality modeling with HSPF are the construction of a conceptual model, mathematical description of the conceptual model, preparation of input data such as time series parameter values, calibration and validation of the model, and application of the model for field conditions. Time series input data can be supplied into the HSPF model by using a stand-alone program or the Watershed Data Management program (WDM) provided in BASINS (Better assessment science integrating point and nonpoint sources). BASINS is a multipurpose environmental analysis system model, which can be utilized by regional, state, and local agencies for conducting water quality based studies. The BASINS system incorporates an open source geographic information system (GIS) (i.e., MapWindow), the national watershed and meteorological data, and the state-of-the-art environmental models such as HSPF, Pollutant Loading Application (PLOAD), and SWAT into one convenient package (USEPA, 2010).

Normally, the development of a HSPF model starts with a watershed delineation process, which includes the setup of digital elevation model (DEM) data in the ArcInfo grid format, generation of stream networks in shape format, and designation of watershed inlets or outlets using the watershed delineation tool built in the BASINS. The HSPF also needs land use and soil data to determine the area and the hydrologic parameters of each land use pattern in the model, which can be done with the land use and soil classification tool in the BASINS. The HSPF is a lumped parameter model with a modular structure. The PERLAND modular represents the pervious land segments over which a considerable amount of water infiltrates into the ground. The IMPLND modular denotes the Impervious land segments over which infiltration is negligible such as paved urban surfaces. Processes involving water bodies like streams and lakes are represented with the RCHRES module. These modules have many

components dealing with hydrological and water quality processes. Detailed information about the structure and functioning of these modules can be found in elsewhere (Donigian and Crawford 1976; Donigian et al. 1984; Bicknel et al. 1993; Chen et al. 1998).

4. Model application

Two watersheds in Mississippi (Upper Pearl River and Yazoo River Basin) were selected for modeling case studies using two hydrologic and water quality models (SWAT and HSPF). Models were calibrated and validated using USGS observed streamflow data for the current conditions and models were applied to predict future climate change scenarios impact on hydrology. Case studies demonstrated how future climate change scenarios impact streamflow from the watersheds.

4.1. SWAT model

The main objective of this case study was to quantify the potential impact of future climate change scenarios on hydrologic characteristics such as monthly average streamflow with in the Upper Pearl River Watershed (UPRW) using the SWAT model. The specific objectives were to: (1) develop a site-specific SWAT model for the UPRW based on watershed characteristics, climatic, and hydrological conditions; (2) calibrate and validate model using USGS observed stream flow data; and (3) develop future climate change scenarios and quantify their impacts on stream flows.

4.1.1. Study area and model development

The SWAT model was developed and applied in the UPRW (7,588 km^2), which is located in Mississippi (Fig. 1). The UPRW covers ten counties (Choctaw, Attala, Winston, Leake, Nesobha, Kemper, Madison, Rankin, Scott and Newton) in Mississippi with predominant land uses of woodland (72%), grassland (20%), urban land (6%) and others (2%).

To develop the SWAT model, this case study utilized national elevation data, which is also called DEM data of 30m x 30m grids to delineate watershed boundary. The STATSGO was used to create distributed soil data input in the model. The land cover data was created using the cropland data layer in the model. The climate data (e.g. daily precipitation, temperature) were used from several weather stations within or near the watershed as maintained by the National Climatic Data Center. The SWAT model allows several potential evapotranspiration estimation method alternatives (e.g. Penman-Monteith, Hargreaves, Priestley-Taylor). This case study utilized the Penman-Monteith method to estimate PET, which requires daily rainfall, maximum and minimum temperatures, relative-humidity, solar radiation, and wind speed data. The additional data needed to simulate the SWAT model using Penman-Monteith PET method were generated by the SWAT model.

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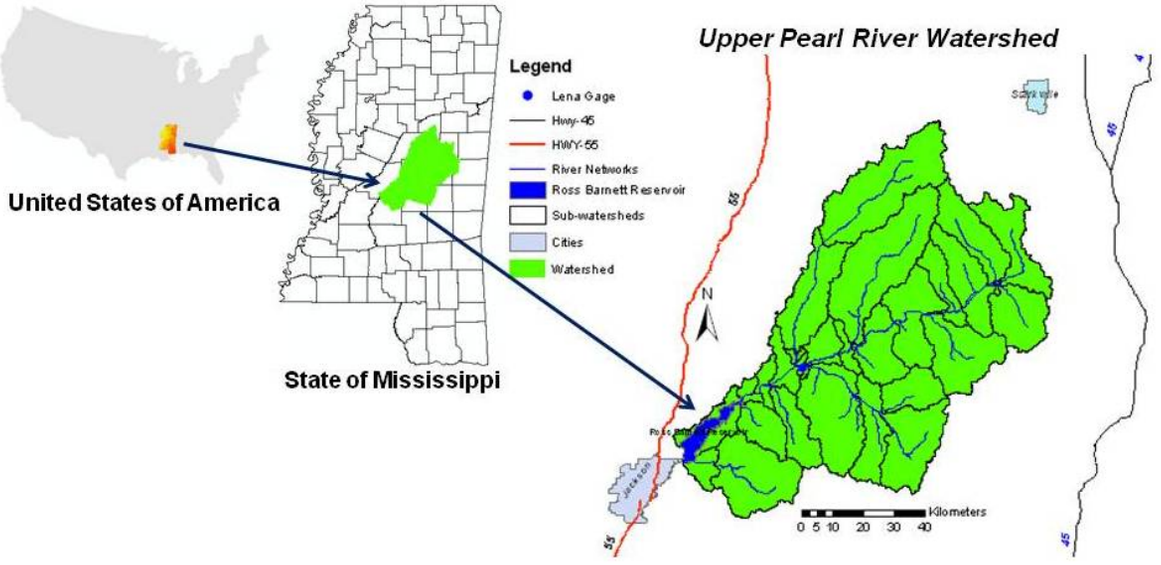


Figure 1. Location map of the watershed showing sub-watersheds and others

4.1.2. Model calibration and validation

The SWAT model predicted monthly streamflow values were compared separately for model calibration and validation periods using three common parameters (coefficient of determination – R^2; Nash–Sutcliffe efficiency index – E; and root mean square error - RMSE). The monthly model performances were ranked excellent for R^2 or E values > 0.90, very good for values between 0.75–0.89, good for values between 0.50–0.74, fair for values between 0.25–0.49, poor for values between 0–0.24, and unsatisfactory for values < 0 (Moriasi et al., 2007; Parajuli et al., 2008, 2009). The RMSE performance has no suggested values to rank, however the smaller the RMSE the better the performance of the model (Moriasi et al., 2007), and a value of zero for RMSE represents perfect simulation of the measured data.

The SWAT model was calibrated (from January 1998 to December 2003) and validated (from January 2004 to December 2009) using field observed monthly streamflow data from the Lena USGS gage station (USGS 02483500) within the UPRW. Model calibration and validation parameters were adopted from previous study (Parajuli, 2010a). Model simulated results showed good to very good performances for the monthly streamflow prediction both during model calibration (R^2 = 0.75, E = 0.70) and validation (R^2 = 0.73, E = 0.51) periods (Fig. 2). The SWAT model predicted monthly streamflow (m^3 s^{-1}) estimated very similar RMSE values (<2% difference) during model calibration (RMSE = 51.7 m^3 s^{-1}) and validation (RMSE = 50.7 m^3 s^{-1}) periods. This case study results were in close agreement with several previous studies that used the SWAT model (Gassman et al., 2007; Moriasi et al., 2007; Parajuli et al., 2009; Parajuli 2010a; Nejadhashemi et al., 2011; Sheshukov et al., 2011).

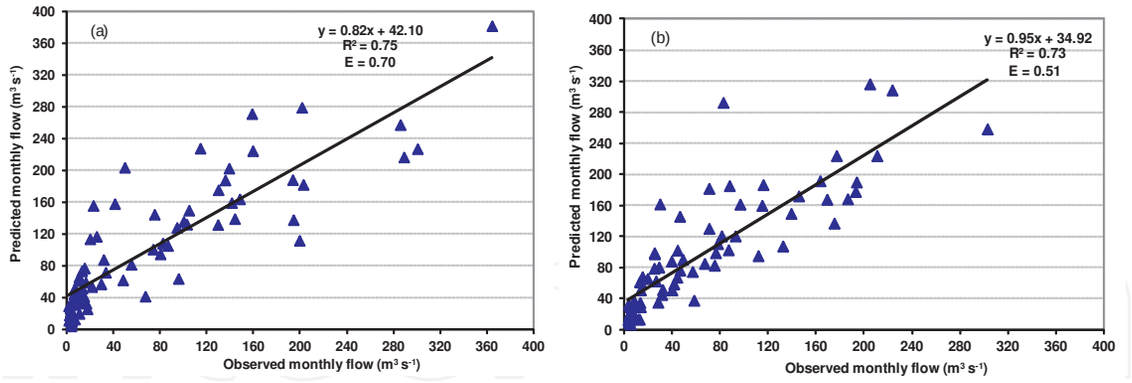


Figure 2. Monthly observed vs. predicted streamflow during (a) calibration and (b) validation periods

4.1.3. Future climate scenarios

The calibrated and validated SWAT model for the UPRW was simulated for an additional 30 years (January 2010 to December 2040) to provide fourteen future climate change scenarios (Table 1). The average streamflow value from the calibrated and validated model was considered as baseline scenario. The future climate change scenarios represented percentage change in the precipitation, temperature and CO_2 concentration values as described in the Table 1. The CO_2 values were adjusted from a baseline value of 330 ppmv (part per million by volume), which is a default value provided in the SWAT model. Two other CO_2 values (495 and 660) were tested in the model considering 50% and 100% increase from the model default value. Percentage changes in the precipitation were simulated for ±20% from the baseline value. Similarly, the model temperature factor was adjusted using +1 and +2 degrees in Celsius from the baseline. The fourteen future climate change scenarios were developed using interaction of three CO_2, three precipitation, and three temperature adjustment values.

The SWAT model results for fourteen scenarios (from Sc1 to Sc14 for Lena gage station) predicted an average maximum monthly stream flow decrease of 57% and average maximum monthly flow increase of 74% from the base simulation (Figure 3). Precipitation increase always had the greatest impact on monthly streamflow from the watershed. A twenty percent increase in precipitation resulted into the greatest impact in the future streamflow prediction. However, increases in CO_2 and temperature accelerated the magnitude of streamflow process.

Scenario 13 with the highest increase in the precipitation (+20%), CO_2 (660 ppmv), and temperature (+2 degree Celsius) had about 74% greater impact on streamflow prediction than the baseline condition (Fig. 3). Other scenarios that had high impact on streamflow prediction were Sc1, Sc4, Sc7, and Sc10. The increase in the temperature had medium impact on streamflow process as shown by Sc3, Sc6, Sc9, and Sc12. However, Sc12 had the greatest impact among medium scenarios as it predicted about 10% greater cumulative monthly streamflow than the baseline condition. Scenarios Sc2, Sc5, Sc8, Sc11, and Sc14 had lower cumulative monthly streamflow than the baseline condition, as they all had decreased precipi-

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tation (-20%). However, Sc14 had the greatest effect on stream flow among all low condition scenarios, due to the highest temperature (+2 degree Celsius) and CO_2 values (660 ppmv).

CO_2 (ppmv)	Precip. (%)	Temp. (adj. °C)	Scenarios	Effect
330	0	0	Base	No
330	+20	0	Sc1	High
330	-20	0	Sc2	Low
330	0	+1	Sc3	Medium
330	+20	+1	Sc4	High
330	-20	+1	Sc5	Low
330	0	+2	Sc6	Medium
330	+20	+2	Sc7	High
330	-20	+2	Sc8	Low
495	0	+2	Sc9	Medium
495	+20	+2	Sc10	High
495	-20	+2	Sc11	Low
660	0	+2	Sc12	Medium
660	+20	+2	Sc13	High
660	-20	+2	Sc14	Low

CO_2 = carbon dioxide, Precip. = precipitation, Temp. = temperature, Sc = scenario

Table 1. Simulated climate change parameters scenarios and effect

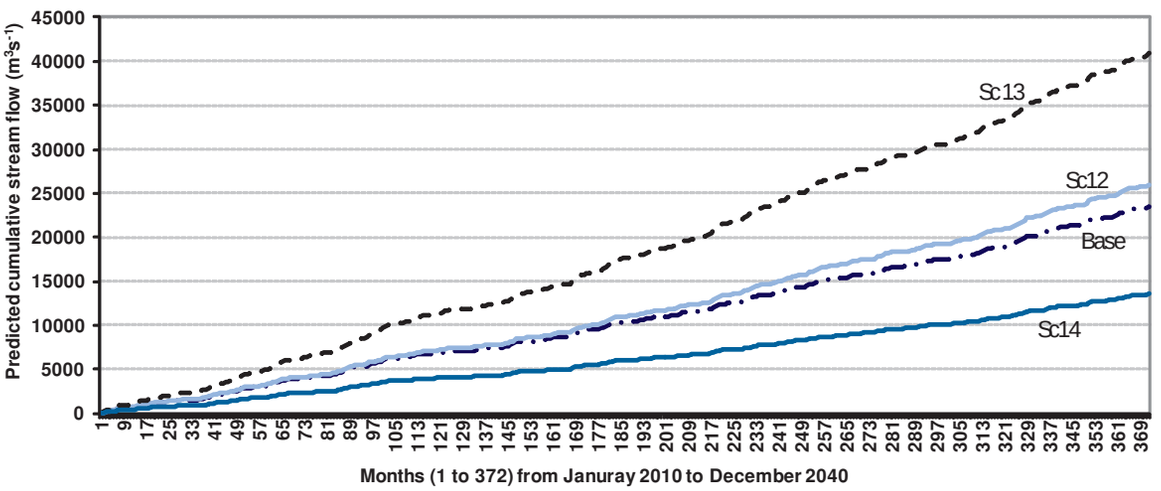


Figure 3. Model predicted cumulative monthly streamflow during thirty years period (2010-2040) showing greater than base condition and lower than base condition scenarios.

4.2. HSPF model

The goal of this case study was to estimate the potential impact of future climate change upon hydrologic characteristics such as river discharge, surface evaporation, and water outflow in the YRB (Yazoo River Basin) using the HSPF model. The specific objectives were to: (1) develop a site-specific model for the YRB based on watershed, meteorological, and hydrological conditions; (2) calibrate the resulting model using existing field data and/or computational data; and (3) create simulation scenarios to project the potential impact of future climate changes upon hydrologic characteristics in the YRB.

4.2.1. Study area and model development

The YRB is the largest river basin in Mississippi, USA and has a total drainage area of 34,600 km^2 (Fig. 4). This basin is separated into two distinct topographic regions, one is the Bluff Hills (about 16600 km^2) and the other is the Mississippi Alluvial Delta (Guedon and Thomas, 2004; MDEQ, 2008; Shields et al., 2008). The Bluff Hills region is a hilly and upland area where streams originate from lush oak and hickory forests and pastures dominate the rural landscape. The Delta Region, on the other hand, is a flat and lowland area characterized by slow streamflow and an extensive system of oxbow lakes.

Data collection for the YRB (HUC 8030208) includes watershed descriptions, meteorological, and hydrologic data. Several agencies are active in the data collection efforts. Most of the data used in this study such as land use, soil type, topography, precipitation, and discharge are from National Hydrography Dataset, U.S. Geologic Survey National Water Information System, and 2001 National Land Cover Data.

Four future climate change scenario data, namely the HADCM3B2, CSIROMK35A1B, CSIROMK2A1B, and MIROC32A1B, were used in this case study. HADCM3, CSIROMK35, CSIROMK2, and MIROC32 are names of climate general circulation models (GCM). The B2 and A1B at the end of the names of the climate change scenarios are the Intergovernmental Panel on Climate Change (IPCC) emission scenarios under which the GCMs were run to produce the individual climate projection. The HADCM3B2 scenario data was obtained from the Hadley Centre for Climate Prediction and Research, United Kingdom. The CSIROMK35A1B and CSIROMK2A1B scenarios data were obtained from the Australian Commonwealth Scientific and Research Organization Atmospheric Research, and the MIROC32A1B scenario data was obtained from the Center for Climate System Research, University of Tokyo National Institute for Environmental Studies and Frontier Research Center for Global Change. More detail information about these climate scenarios are available at: http://www-pcmdi.llnl.gov/ipcc/model_documentation/ipcc_model_documentation.php. These four scenarios data involve monthly air temperature and precipitation for a period from 2000 to 2050, which were generated by GCMs and the Center for Climate System Research National Institute for Environmental Studies and Frontier Research Center for Global Change (University of Tokyo). These data were scaled to the 8-digit HUC watersheds for different regions. For the YRB watershed, the 8-digit HUC was 08030208. A descriptive statistics for these four scenarios data showed the amount of precipitation from high to low order as: CSIROMK35A1B > HADCM3B2 > CSIROMK2A1B > MIROC32A1B, whereas the magnitude

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of air temperature from high to low order as: MIROC32A1B > CSIROMK35A1B > CSIR-OMK32A1B > HADCM3B2.

The HSPF model for this case study was developed using the PERLND, IMPLND, and RCHRES modules that are available in HSPF. The PWATER section of the PERLND module is a major component that simulates the water budget, including surface flow, inter-flow and groundwater behavior. The HYDR section of the RCHRES module simulates the hydraulic behavior of the stream.

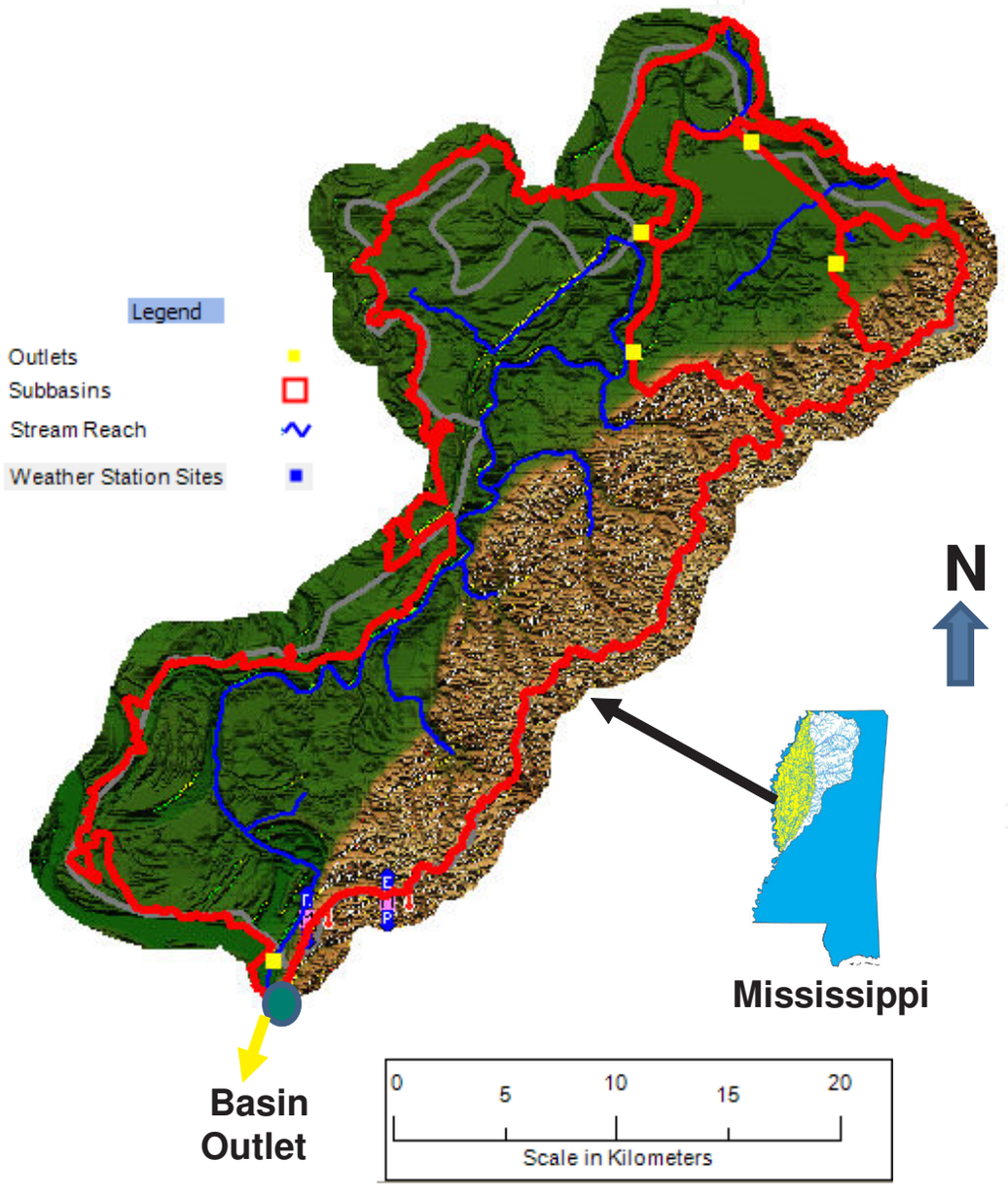


Figure 4. Location of modeled area in the Yazoo River Basin, Mississippi.

4.2.2. Model calibration and validation

Model calibration involves adjusting input parameters within a reasonable range to obtain a best fitness between field observations and model predictions. Model validation is a process of validating the calibrated model by comparing the field observations against the model predictions without changing any input parameter values. Table 2 shows a comparison of the observed and predicted annual water outflow volume. The annual differences in errors between the observed and predicted water outflow volumes were about 6% and were, therefore, acceptable (Bicknell et al., 2001). With prediction = 0.97*observation and R2 = 0.98 and E = 0.96, we determined that an excellent agreement was obtained between the field observations and model predictions during the model calibration process.

Comparison of annual water outflow between the observations and predictions for a time period from January 1, 2005 to December 31, 2010 during the model validation process was given in Table 2. The regression equation predictions = 0.97*observation and R^2 = 0.99 and E = 0.97 verified the excellent agreement between the model predictions and the field observations during the model validation process.

Year	Simulated Outflow (m^3)	Observed Outflow (m^3)	Percent Different
Model Calibration			
2000	1.77E+09	1.75E+09	0.88
2001	2.05E+09	1.92E+09	6.34
2002	1.93E+09	1.93E+09	-0.37
2003	1.15E+09	1.16E+09	-0.34
2004	2.00E+09	1.90E+09	5.58
Total	**8.90E+09**	**8.66E+09**	**2.68**
Model Validation			
2005	1.32E+09	1.30E+09	1.64
2006	1.33E+09	1.35E+09	-2.10
2007	1.20E+09	1.19E+09	1.13
2008	9.71E+08	9.47E+08	2.54
2009	1.96E+09	1.82E+09	7.40
Total	**6.78E+09**	**6.62E+09**	**2.50**

Table 2. Comparison of the simulated and observed annual water outflow volumes during model calibration and validation.

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4.2.3. Past and future climate change

Comparison of mean annual water yields between the past 10 years (2001-2011) and the future 40 years (2011-2050) for the four climate projections indicates that water yields will continue to decline (Table 3). The percent change in mean annual water yield varied from 29.47% for the CSIROMK35A1B projection to 18.51% for the MIROC32A1B projection, with four climate projections indicating continuing declines out to 2050. The same decline trends were observed for maximum annual water yields (Table 3). The declines in mean and maximum annual water yields occurred primarily due to the projected precipitation decrease. Mixed results were found for the mean annual evaporative loss (Table 3). The CSIROMK2B2 projection indicated a long-term increase while the other three projections indicated a long-term decrease in evaporative losses. Further work is thus necessary to better determine how evaporative losses will respond in the future.

Changes of monthly minimum, mean, and maximum in water discharges and yields for the four climate projections during the 40-year simulation period (2011-2050) are given in Figs. 5 and 6. The monthly minimum, mean, and maximum water discharges and yields varied among the four climate projections and changed from year to year within each projection. In general, the MIROC32A1B projection had highest monthly minimum, mean, and maximum water discharges and yields in most of the years during the 40-year simulation, which occurred because the MIROC32A1B projection had highest annual precipitation during the same simulation period (Table 3).

Scenario	Precipitation (cm)			Evaporative Loss (m^3)			Water Yield (m^3)		
	Past 10 Years (2001 to 2010)	Future 40 Years (2011 to 2050)	% Change	Past 10 Years (2001 to 2010)	Future 10 Years (2011 to 2050)	% Change	Past 10 Years (2001 to 2050)	Future 10 Years (2011 to 2050)	% Change
	Annual Mean								
HADCM3B2	0.017	0.015	-10.23	92.80	84.40	-9.95	40000.00	32282.00	-23.91
MIROC32A1B	0.016	0.015	-10.01	99.90	86.89	-14.97	37000.00	31222.00	-18.51
CSIROMK35A1B	0.019	0.017	-12.69	125.00	100.96	-23.81	53300.00	41169.00	-29.47
CSIROMK2B2	0.016	0.016	0.10	96.20	104.62	8.05	34800.00	32787.00	-6.14
	Annual Maximum								
HADCM3B2	1.052	0.754	-39.45	484.00	330.25	-46.56	2160000.00	129412.00	-1569.09
MIROC32A1B	1.161	0.842	-37.79	618.00	372.10	-66.08	2150000.00	148377.00	-1349.01
CSIROMK35A1B	1.346	1.088	-23.73	580.00	438.07	-32.40	2160000.00	205767.00	-949.73
CSIROMK2B2	0.991	0.749	-32.33	488.00	371.37	-31.41	2160000.00	130590.00	-1554.03

Table 3. Comparison of the sum and mean values for precipitation, evaporative loss, and water yield between the past and future 10 years.

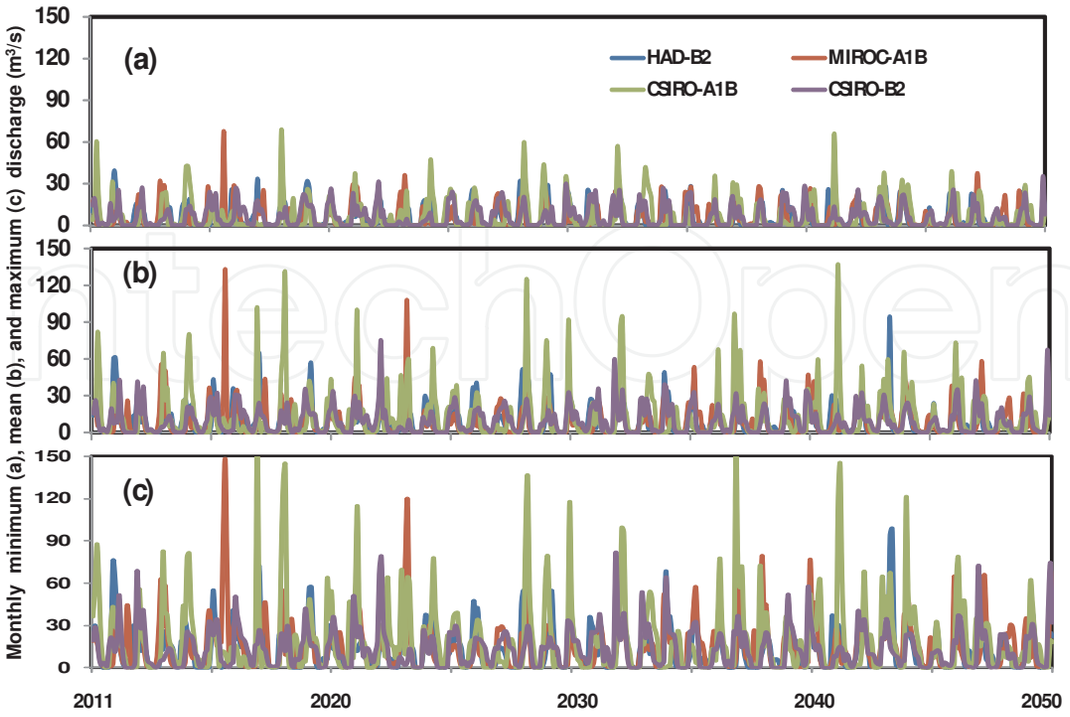


Figure 5. Simulated monthly minimum (a), mean (b), and maximum (c) discharge for the four simulation scenarios.

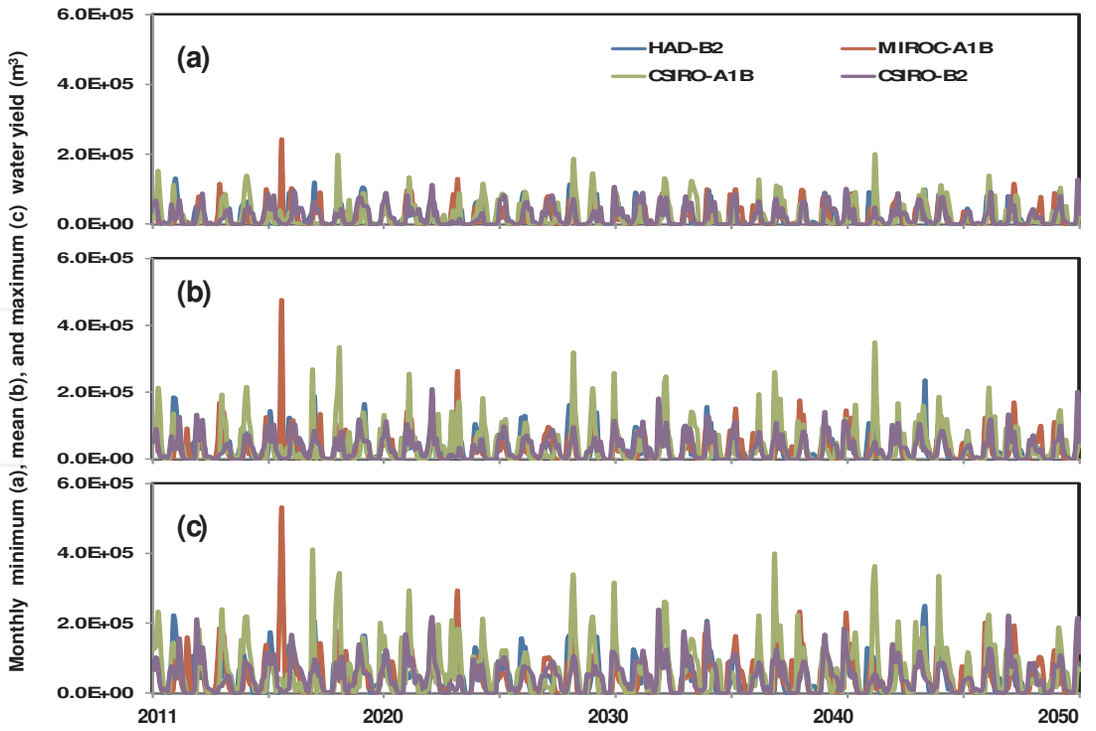


Figure 6. Simulated monthly minimum (a), mean (b), and maximum (c) water outflow volume for the four simulation scenarios.

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5. Conclusions

Two models (SWAT and HSPF) commonly used in hydrological and water quality studies were applied here in two large scale watersheds (UPRW and YRB) in the state of Mississippi. Models were calibrated and validated using USGS observed streamflow data. The long-term hydrological impacts due to future climate change scenarios were assessed using the SWAT and HSPF models.

For one case study, simulated mean monthly streamflow results for the calibrated and validated SWAT model provided good to very good fits (R^2 and E values from 0.75 to 0.51) to USGS monthly observed streamflow data. Fourteen future climate change scenarios were developed using interaction of precipitation, CO_2, and temperature adjustment values in the SWAT model. The scenario with the highest increase in the precipitation (+20%), CO_2 (660 ppmv), and temperature (+2 degree Celsius) had about the greatest (> 74%) impact on streamflow simulation when compare with the baseline condition. Interaction of temperature adjustment and CO_2 factors had a medium and low impact respectively during thirty year's model simulation period in this study.

Another case study examined the impact of climate change on future water discharge, evaporation, and yield in the YRB using the BASINS-HSPF model. The model was calibrated using observed data from a five-year (2001 to 2004), and validated using observed data from another five-year (2005 to 2010). Excellent agreements were obtained between the model predictions and the field observations for model calibration and validation.

Four future climate scenarios (or projections) - CSIROMK35A1B, HADCM3B2, CSIROMK2B2, and MIROC32A1B were used to investigate water discharge, evaporative loss, and water outflow responses to predicted precipitation and air temperature changes over a 50-year period from 2001 to 2050. Comparison of simulation results between the past 10 years (2001-2010) and the future 40 years (2011-2050) shows that the mean and maximum annual water yields declined due to the projected precipitation decrease. In general, the MIROC32A1B projection had the highest monthly minimum, mean, and maximum water discharges and yields in most of the years during the 40-year simulation period (2011-2050). This projection had the highest projected annual precipitation. Results suggest that the projected precipitation had profound impacts upon water discharge and yield in the YRB.

Spatial data used in the models may have potential sources of errors. For example, the DEM data are used to delineate watershed boundary are available in different resolutions. Similarly, use of land use, soils and weather data may have some spatial errors, which can influence the hydrologic and climate change impact. However, these results will only have relative influence in model simulated results. This book chapter provided review of several watershed and water quality models and two case studies to evaluate future climate change impact on hydrology using two models.

Acknowledgement

The part of the case study research presented in this book chapter is based on work supported by the Special Research Initiatives (SRI) and Mississippi Agricultural and Forestry Experiment Station (MAFES) at Mississippi State University.

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