12-2011

Geospatial Tools and Techniques for Watershed Management Using SWAT 2009

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GEOSPATIAL TOOLS AND TECHNIQUES FOR WATERSHED MANAGEMENT USING SWAT 2009

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy in Biological Engineering

By

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Abstract

In this study, geospatial tools and techniques were developed to support specific aspects of watershed pollution management, such as quantifying land-use change (LUC) impacts, prioritizing subwatersheds, and communicating field-scale impacts, using the soil and water assessment tool 2009 (SWAT 2009) model.

For the land-use change objective, a geospatial tool titled SWAT2009_LUC was developed that enables SWAT modelers to prepare specific input files for simulating concurrent land-use changes during the SWAT 2009 model simulations. Testing of the tool for the Illinois River Drainage Area in Arkansas (IRDAA) watershed showed that the tool accurately represented temporal land-uses within the model. Model simulations with and without the activation of the LUC module showed that groundwater was under predicted by up to 15%, while surface runoff was over predicted by up to 13% at the subwatershed scale when a single land use layer was used. Overall, the results showed that activating LUC module using the SWAT2009_LUC tool exhibits hydrological simulations that are different from those resulting from a single land use layer.

For the subwatershed prioritization objective, a modeling approach was developed for prioritizing the 12-digit hydrologic unit code subwatersheds of the IRDAA watershed using the SWAT 2009 model output for sediment, total phosphorus (TP), and nitrate-nitrogen (NO_3-N). The model was calibrated and validated at seven locations for total flow, base flow and surface runoff, and at three locations for water quality outputs. A multi-objective function consisting of percent relative error (RE), Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), coefficient of determination (R^2), and ratio of the root mean square error to the standard deviation of measured data (RSR) was used to guide model evaluations. The resulting priority subwatersheds comprised only 24% of the total area of the watershed but contributed 49% of sediment, 33% of TP, and 27% of NO_3-N simulated loadings. Statistical relationships between priority subwatersheds and their various characteristics assisted with supporting the prioritization results. For the IRDAA watershed, this

approach produced results that could assist watershed management agencies in optimizing allocation of limited resources in addressing water quality issues.

For the third objective, Field_SWAT, a simple graphical user interface (GUI) driven tool, was developed to map SWAT simulations from hydrological response units (HRUs) layer to a user-defined field boundaries layer. The SWAT model divides a watershed into HRUs based on unique land cover, soil type and slope. HRUs are a set of discontinuous land masses that are spatially located in the watershed but their responses are not tied to any particular field. The Field_SWAT tool ingests SWAT outputs and helps in visualizing them at field-scale using four different spatial aggregation methods. The tool was applied for mapping SWAT model's annual runoff and sediment outputs from 218 HRUs to 89 individual field boundaries in an agriculturally dominated watershed in Northeast Arkansas. Area-weighted spatial aggregation method resulted in most suitable mapping between HRU and field outputs. This research demonstrates that Field_SWAT could potentially be a useful tool for field-scale targeting of conservation practices and communicating model outputs to watershed managers and interested stakeholders.

This dissertation is approved for recommendation
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Acknowledgements

This dissertation would not have been possible without the steadfast mentorship of my major advisor, Dr. Dharmendra Saraswat. His guidance, and support from the start to finish enabled me to develop a comprehensive understanding of my research area. He helped me think and write carefully, to pay attention to words, and to ask questions. I have always looked up to his unwavering hard-working nature, passion for technology, and diversity of thought. For everything you have done for me, Dr. Saraswat, I thank you.

I would like to thank my committee members: Drs. Sreekala G. Bajwa, Jackson Cothren, and Thad Scott for serving on my research committee and their efforts in guiding me at various stages of my doctoral degree. My committee members also trained me in the areas of remote sensing (Dr. Bajwa), geo-statistics (Dr. Cothren), and water quality (Dr. Scott) which were the key elements of this dissertation.

My inquiry in watershed modeling over the past 4 years has made me realize that a model cannot be setup without the intensive data collection efforts of multiple individuals and agencies. I, therefore, appreciate the efforts of all individuals who directly or indirectly provided the much-required data for modeling. Additionally, I would like to acknowledge the Arkansas Natural Resources Commission (ANRC) and the University of Arkansas Department of Biological and Agricultural Engineering for providing financial resources to conduct the studies reported in this dissertation.

The SWAT development team was an invaluable asset through the various stages of this research. Particularly, I would like to express my sincere gratitude to Dr. Raghavan Srinivasan, Dr. Jeff Arnold, Ms. Nancy Sammons, and Dr. Mike White, for their prompt assistance with questions related to ArcSWAT interface, and the SWAT algorithm.

I am also grateful to the Arkansas high performance computing center (AHPCC) for providing me with resources that expedited computationally intensive parts of this research. Dr. David

Chaffin, Dr. Wesley Emeneker, and Mr. Jeff Pummill at the AHPCC deserve a special mention for patiently sharing their technical expertise when needed the most.

This is a great opportunity to express my respect for the University of Arkansas (UA), Department of Biological and Agricultural Engineering, and the UA Graduate School for providing the necessary infrastructure to complete my doctoral degree. I am especially thankful for the help received from Ms. Patricia Kirkwood (engineering and math librarian) and the inter-library loan department at the UA Libraries. Thanks also go out to all my friends and colleagues for their valuable friendship over the years. Special thanks to former fellow graduate student, Mansoor Leh for being so generous with his time whenever I hit a snag in GIS.

Finally, and most importantly, I would like to thank my parents, Anant and Archana Pai, brother and sister in-law, Yogesh and Arti Pai, for having faith in me and supporting my academic ambitions. I would also like to thank my in-laws, Muralidhara and Jyothi, for their prayers and belief in me. Words cannot adequately express the love, support, and patience of my wife, Divya. Your constant encouragement inspired me to keep going.

This dissertation is dedicated to God and the loving family that I have been blessed with.

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Chapter 3

Pai, N., D. Saraswat and M. Daniels. 2011. Identifying priority subwatersheds in the Illinois River Drainage Area in Arkansas watershed using a distributed modeling approach. Trans. ASABE 54(6): In Press.

Chapter 4

Pai, N., D. Saraswat and R. Srinivasan. 2011. Field_SWAT: a tool for mapping SWAT output to field boundaries. Computers & Geosciences In Press. doi:10.1016/j.cageo.2011.07.006.

Chapter 1

Introduction and Background

1.1 Role of Models in Watershed Management

The spatial and temporal variation of environmental and water resource problems such as upland erosion, agrochemical runoff, deterioration of stream and lake water quality, and land-use changes are now better understood through hydrological/water quality (H/WQ) watershed model simulations (Singh and Frevert, 2006). Models are also commonly used to quantify environmental impacts due to of various watershed management policies (Arabi et al., 2006). Several H/WQ watershed models exist, however, distributed-parameter watershed models are being particularly considered useful for simulating large watersheds because they can better represent spatial heterogeneity of various causal factors in a single framework (Borah and Bera, 2003). Availability of online geospatial data sources, remote sensing, and radar technology for measurement of precipitation has opened up opportunities for advancement of existing distributed models (Vieux, 2004). Therefore, hydrologists, scientists, and engineers are involved in developing, modifying, and enhancing H/WQ models to better represent reality and improve applicability.

A primary problem that exists with current H/WQ watershed models is that they are complex (White et al., 2009b). For models to become practical tools in addressing environmental and water resource problems, Singh and Frevert (2006) suggest that model outputs will have to be simplified with a clear statement of what they can and cannot do. Indeed, decision makers are always looking for quantitative information from H/WQ distributed models to devise simple and pragmatic management strategies. Simple tools and techniques are required that can enable a watershed model to answer some of the common issues faced by watershed managers.

1.2 Dissertation Problems

Quantifying impacts due to land-use changes (LUCs); identifying and allocating financial, and personnel resources in high priority areas; and visualizing and disseminating model results to stakeholders represent some of the common difficulties faced in efficient watershed management. These inter-connected model applications serve as key goals in restoration plans for various impaired watersheds in the U.S. and worldwide. H/WQ watershed models are useful in these applications because they inform watershed managers in advance about implementing effective management solutions. Several watershed models are available and their ability to simulate continuous long-term watershed processes under various physiographic and climatic conditions has been demonstrated (Borah and Bera, 2004). However, their applicability to guide watershed managers in addressing concerns mentioned above remains an active area of research (Tripathi et al., 2003; Kannan et al., 2005; Santhi et al., 2006; Robertson et al., 2009; Schilling et al., 2009). Particularly, the soil and water assessment tool (SWAT) H/WQ watershed model recommended by the U.S. environmental protection agency (EPA), has received wide attention as reflected by some 800+ articles published in peer-reviewed literature (SWAT, 2011). This dissertation uses the SWAT model to find practical solutions to problems related to watershed management.

The first problem is related to assessing impacts of LUCs on watershed hydrology. Temporal LUCs, either due to urbanization or deforestation have been widely reported to influence the water cycle (e.g. Miller et al., 2002), sedimentation (e.g. Ouyang et al., 2010), and agrochemical losses (e.g. Ahearn et al., 2005) in watersheds. Quantifying impacts due to LUCs has always been a challenging exercise for modelers because of its temporal variability (Schilling et al., 2009) and ability to confound with other management practices (Chiang et al., 2010). In fact, understanding hydrological alterations resulting from LUCs have been identified as a major research-need (DeFries and Eshleman, 2004) and its quantification has become an integral aspect of many catchment-scale water assessment studies (Calder, 1999).

In modeling studies, pertaining to quantification of LUC impacts, researchers have replaced current land-uses with alternatives in the model (Fohrer et al., 2001; Miller et al., 2002). Assessment of futuristic LUC impacts have also been conducted by using projected land-use geospatial datasets in calibrated SWAT models (e.g. Kalin and Hantush, 2009; Tong et al., 2009). Collectively, the knowledge gained from these studies has improved modeling algorithms and our overall understanding of LUC impacts at various spatial and temporal scales. However, previous LUC assessments used a single snapshot land-use layer to obtain model responses. This assumes that land-use characteristics have remained constant over the modeling period, which can be unrealistic for watershed in which land-use changes are occurring.

Recognizing this limitation in the SWAT model, a LUC module was incorporated in the latest version, SWAT2009 and was briefly introduced by Arnold et al. (2010). The module has the capability to provide quantitative answers to LUC-impact questions that watershed managers may have; yet, its sensitivity for simulating the impacts of LUCs remains untested. Chiang et al. (2010) used the LUC module to separate out water quality impacts resulting from land use changes and implementation of conservation practices, while Saraswat et al. (2010) used the module without comparing its efficacy. There is a need to study the responses of SWAT 2009 model with and without the LUC module, so that it can provide valuable insight for SWAT modelers and help in evaluating if activating this module would be a worthwhile effort for their study area. In addition, land-use changes are manifested in the LUC module through updating area fractions of hydrological response units (HRUs). HRUs are the finest division of landscape in the SWAT model. Considering that the number of HRUs in the SWAT model can range from 100s to 1000s, calculating area fractions multiple times would be laborious and time consuming. This can limit the usage of LUC module by the modeling community. Hence, there is a need to develop an automated geospatial tool that ingests multiple land-use/land-cover layers, develops necessary input files, and activates the LUC module in SWAT 2009.

The second problem addressed in this dissertation is related to identifying priority areas in a watershed. Effectively allocating resources in an impaired watershed is an important concern for watershed managers (Duda and Johnson, 1985). Although reducing nutrient loading from all subwatersheds would provide a comprehensive way to achieve water quality goals, it would not be the most efficient strategy because not all subwatersheds contribute equal quantities of nutrients to local streams (Dickinson et al., 1990). The focus of this study is to develop a simulation approach for prioritizing subwatersheds and to evaluate its performance in the Illinois River Drainage Area in Arkansas (IRDAA) watershed in Northwest Arkansas where adequate, existing water quality monitoring and input data exists. It also provides a "real world setting" where urbanization has been extensive during the past 10 - 15 years and management of point and nonpoint sources of pollution has undergone considerable change (Sharpley et al., 2009; Haggard, 2010; Scott et al., 2011).

In addition, past prioritization studies have not validated the order of priority resulting from simulation models. Typically, models are calibrated at one or more locations using monitoring data. Watershed managers and stakeholders may remain unconvinced with model-generated priority subwatersheds because the model has not been calibrated or validated at all subwatershed outlets. In fact, Refsgaard (2001) stressed that modelers need to make better use of additional information for validation that will help strengthen the confidence in distributed model outputs at internal locations. Consequently, there is a need to develop an approach to identify and validate priority subwatersheds using surrogate data sources. The IRDAA watershed provides an ideal case study to test and develop a suitable prioritization approach because (a) it is impaired due to both point and non-point sources of pollution and (b) a long-term monitoring data at multiple sites exists.

The third problem in this dissertation is related to visualizing and communicating field-scale model outputs. Simplifying watershed model results and communicating them to stakeholders is critical to obtain feedback and subsequently, translate model results into pragmatic pollution-abatement solutions (Singh and Frevert, 2006). The SWAT model divides a watershed into HRUs based on unique land cover, soil type, and slope in each subwatershed. HRUs are a set of discontinuous landmasses in the watershed and their responses are not tied to any particular field. An HRU may either be smaller than a field or encompass multiple fields. On contrary, the unit for implementation of many agricultural conservation practices is typically for a field (Daggupati et al., 2011). This renders the default HRU output from the SWAT model of little use for any practical purposes.

In fact, the spatial structure of HRUs within the SWAT framework remains complicated and hard to visualize even for the modeling community. It is not surprising that most published SWAT studies have evaluated model outputs either at the watershed outlet or at subwatershed boundaries. Nonetheless, HRU-scale outputs are important as simulations in SWAT originate at this scale (Neitsch et al., 2005) and are closest when trying to relate with field-scale data (White et al., 2009a). To validate HRU-scale outputs with field-data, Veith et al. (2008) delineated a 39.5 ha watershed (containing 24 row-cropped fields) with only 123 HRUs. Their approach was to delineate an HRU for every unique soil category, thus allowing direct spatial mapping between fields and HRU output. However, for larger watersheds, which have multiple and diverse land uses, soil types and topography, the spatial structure of HRUs can get complicated and its output is hard to comprehend. Recently, the SWAT model has been used in field-scale runoff (Anand et al., 2007), sediment, and nutrients (Gollamudi et al., 2007) assessment studies. In these studies, the model was setup for individual fields by using the field edges as the watershed boundary while field scale monitoring data was used for calibration and validation. Although this approach is successful, it could be a tedious process for larger watersheds.

Interfaces available for the SWAT model are very complex because they are designed to represent detailed basin-scale management operations and offer extensive configuration options (White et al., 2009a). Simpler tools are required for conservation planners to use SWAT model results at finer scales (Veith et al., 2008). HRU outputs were used to identify critical source areas (White et al., 2009b; Ghebremichael et al., 2010), albeit without validation which can result in lack of confidence in the outcomes (Refsgaard, 2001). Such efforts can benefit from a method that maps the HRUs outputs to user-defined field boundaries and allows comparing HRU scale output with edge-of-field measurements. Therefore, a geospatial tool is required to map HRU-scale simulations to a user-defined field boundaries layer for understanding HRU-scale output and for communicating model outputs to watershed managers and interested stakeholders.

1.3 Objectives and Hypotheses

The overarching goal of this research is to find practical solutions to problems related to watershed management. The SWAT 2009 model was evaluated for land-use change sensitivity, priority subwatershed identification, and field-scale mapping of output. The following specific objectives and hypotheses will be addressed in this dissertation:

Objective 1. Evaluate sensitivity of SWAT2009 model to concurrent land-use changes. Develop a methodology and an automated tool to allow SWAT modelers to incorporate multiple land-uses during simulation.
Hypothesis 1. Incorporation of concurrent land-use change during SWAT model run will allow modelers to incorporate and differentiate impacts due to land-use changes in watersheds.

Objective 2. Develop an approach to prioritize subwatersheds based on sediment and nutrient contribution and corroborate results using surrogate datasets.
Hypothesis 2. Identifying priority subwatersheds based on its individual contribution results in efficient prioritization while validating priority subwatersheds using additional surrogate data sources improves confidence in model-generated priorities.

Objective 3. Develop a methodology to map HRU outputs from SWAT model to field boundaries to understand field-scale impacts and communicate outputs to stakeholders.
Hypothesis 3. Mapping abstract HRU outputs to real-world field boundaries will allow better visualization and communication of SWAT model outputs.

1.4 Dissertation Organization

Including this introductory and background chapter, this dissertation is divided into six chapters. Chapter 2 details a study conducted to assess the sensitivity of the SWAT 2009 model to land-use changes and development of the SWAT2009_LUC geospatial tool to activate the LUC module in SWAT 2009. Chapter 3 describes the setup, multi-site calibration, and validation of the SWAT model for the IRDAA watershed following which a subwatershed prioritization and its validation is explained. Chapter 4 provides details of the development of the Field_SWAT tool that can be used to map and visualize the HRU output from the SWAT model to user-defined boundaries. Chapter 5 provides a synthesis of the key results from individual studies and future directions. Finally, chapter 6 lists all the references that have been cited in this dissertation.

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Chapter 2

SWAT2009_LUC: A Tool to Activate the Land Use Change Module in SWAT 2009

2.1 Abstract

In watersheds where land use and land cover changes take place over the modeling period, using a single land use geospatial dataset is not a true representation of the watershed condition. This article describes development of SWAT2009_LUC, a computer-based, geospatial tool that ingests multiple land use/land cover geospatial datasets and other associated information interactively and activates the land use change (LUC) module in the latest release of the Soil and Water Assessment Tool (SWAT 2009). The geospatial tool was tested in an urbanizing watershed in northwest Arkansas by using three temporal land use geospatial data layers acquired during 1999, 2004, and 2006. The results show that the land use distribution generated by the tool was consistent with the input land use layer for each year and was updated correctly during the model run. Model simulations with and without the activation of the LUC module showed that groundwater was underpredicted by up to 15%, while surface runoff was overpredicted by up to 13% at the subwatershed scale when a single post-development land use layer was used. Overall, the results showed that activating the LUC module using the SWAT2009_LUC tool improves the spatial and temporal hydrological responses from the SWAT 2009 model.

Keywords. *Change, Geospatial, Hydrology, Interface, Land use, Modeling, SWAT.*

2.2 Introduction

Among the various causes of water quality degradation, land uses can have one of the greatest impacts. Temporal land use changes (LUCs) either due to urbanization or deforestation have been widely reported to influence the water cycle (e.g., Miller et al., 2002), sedimentation (e.g., Ouyang et al., 2010), and agrochemical losses (e.g., Ahearn et al., 2005) in watersheds. Past studies have reported an empirical relationship between land use distribution and water quality at the watershed scale (Haggard et al., 2007; Migliaccio et al., 2007) and demonstrated that certain LUC, such as urbanization, can even mask the effect of any concurrent conservation practices (Chiang et al., 2010). Understanding hydrological alterations resulting from land use changes has been identified as a major research need (DeFries and Eshleman, 2004), and its quantification has become an integral aspect of many catchment-scale water assessment studies (Calder, 1999; DeFries et al., 2004).

Physically based models are useful tools for such assessments since they provide a comprehensive yet cost-effective way to evaluate the relationship between long-term land use changes and hydrologic processes in a watershed. For instance, previous studies conducted using the Long-Term Hydrologic Impact Assessment (L-THIA) model reported that an increase in imperviousness greatly increased average annual surface runoff (Bhaduri et al., 2000; Choi et al., 2005). Similarly, Twine et al. (2004) used the Integrated Biosphere Simulator (IBIS) model for the entire Mississippi River basin to quantify the hydrological impacts of deforestation and changing grass cover to crop cover. While such modeling studies help decision-makers target regional-scale impacts, land use change may often be a local phenomenon and have disproportional subwatershed-scale impacts. Distributed models offer an advantage in such scenarios because they have the necessary spatial resolution to represent localized land use changes. Among various distributed models, the physically based Soil and Water Assessment Tool (SWAT) has found wide application in various watershed assessment studies (Borah and Bera, 2004).

Land use change assessment studies using the SWAT model have been previously reported (Fohrer et al., 2001; Lin et al., 2009; Ghaffari et al., 2010; Ouyang et al., 2010; Wang and Kalin, 2011). In these studies, researchers replaced current land uses with alternatives in the model to understand and quantify hydrological and water quality impacts. Assessment of futuristic LUC impacts have also been conducted by using projected land use geospatial datasets in calibrated SWAT models (e.g., Kalin and Hantush, 2009; Tong et al., 2009). Collectively, the knowledge gained from these studies has improved modeling algorithms and our overall understanding of LUC impacts at various spatial and temporal scales. However, use of a single land use layer in previous LUC assessments could result in stationarity of model responses. Accurate model predictions depend, in part, on how well matched the watershed responses are to the temporal resolution of land use input data. White and Chaubey (2005) observed that changing land uses could alter the hydrology and sedimentation in a watershed; however, this information is unknown to a model that is operating based on a single land use geospatial dataset. This was especially critical in their study area because the SWAT model received land use information from a single pre-development land use layer, thereby introducing a source of additional uncertainty.

Recognizing this limitation in SWAT, a LUC module was incorporated into the latest version, SWAT 2009, and was briefly introduced by Arnold et al. (2010). A detailed discussion of the mechanism by which the LUC module represents temporal land use is presented in the next section. In spite of this much-required enhancement to SWAT, only two studies known to us have thus far made use of this module (Chiang et al., 2010; Saraswat et al., 2010). This could be attributed, in part, to the intensive input data requirement to activate this module. The module requires fractional areas of every hydrological response unit (HRU), the finest subdivision of the SWAT model, each time the land use is updated. Considering that in medium- to large-scale watersheds, the number of HRUs can range from a few hundred to thousands, updating the fractional areas in response to multiple years of land use datasets available for a SWAT project could be a daunting task and prone to manual errors. Hence, there is a need for an automated tool that can accurately produce the necessary input data files required to activate the LUC module. Another factor that may have contributed to the lack of usage of LUC module is the fact that its applicability has not yet been evaluated. Chiang et al. (2010) used the LUC module to separate out water quality impacts resulting from land use changes and implementation of conservation practices, while Saraswat et al. (2010) used the module without comparing its efficacy. A focused study comparing model hydrological responses with and without the LUC module promises to provide valuable insight for SWAT modelers and help in evaluating if activating this module would be a worthwhile effort for their study area.

This study has two major objectives: (1) to develop a user-friendly computer-based application to assist modelers in creating input files required to activate the LUC module, and (2) demonstrate the LUC module's usefulness for watersheds where land use has changed during the modeling period. Results obtained from this study should provide the necessary tools, demonstrate applicability, and thereby increase usage of the LUC module in SWAT 2009.

2.3 LUC Module Concept

SWAT is a distributed watershed model that is capable of calculating watershed processes for all homogeneous areas within a watershed. To support this task and prepare the necessary input files, the model's algorithm is integrated with a geographical information system (GIS) using an interface called ArcSWAT (Winchell et al., 2008). ArcSWAT first divides a watershed into smaller areas called subwatersheds using either user-defined thresholds or user-defined boundaries. Using a GIS-based overlay operation, the subwatersheds are further divided into homogeneous areas called HRUs, which are assumed to have the same land use, soil, and slope (Pai et al., 2011). Because of the heterogeneity within a subwatershed, the same unique combination of land use, soil, and slope is found in multiple locations. Consequently, HRUs tend to be fragmented in nature, as demonstrated by Pai et al. (2011).

Availability of detailed land use, soil, and slope GIS geospatial datasets can result in too many unique combinations and increase the number of HRUs. For instance, a subwatershed with four land use types, ten soil types, and four slope classes will result in 160 ($4 \times 10 \times 4$) HRUs. This multiplier effect substantially increases the computational time, which in turn may adversely affect the success of modeling projects. To mitigate this situation, ArcSWAT provides an option for reducing the number of HRUs by using threshold percentages. Threshold percentages, provided separately for land use, soil, and slope, result in merging of those land uses, soils, and slope classes that occupy less than a predetermined percentage area within every subwatershed.

Subsequently, using relevant geospatial input layers, ArcSWAT parameterizes each HRU with several specific characteristics, such as its area, slope, land use, soil properties, etc. Of particular interest in this study is the area of the HRU calculated by ArcSWAT. For each HRU, the interface calculates the number of cells that have a unique combination of land use, soil, and slope and divides this by the total number of cells within a subwatershed to output the fractional area. This fractional area, also termed as HRU_FR in the model, ranges from 0 to 1, with a higher number indicating larger occupation in the subwatershed. For instance, a value of 0.1 indicates that the HRU occupies 10% of the subwatershed area. The HRU fractional area and its land use, in combination, reflect the land use distribution of the watershed at that spatial scale.

In the newer version of the SWAT model (SWAT 2009), the LUC module allows the user to update land use distribution by updating the HRU_FR variable during the model run. This process could be better understood using a simplified hypothetical scenario, as illustrated in figure 2.1. Consider a subwatershed with three HRUs (HRU-1, HRU-2, and HRU-3) in 1992 and 1999. In the year 1992, let us say that HRU-1, HRU-2, and HRU-3 encompassed forest, urban, and pasture areas and occupied 30%, 40%, and 30% of the subwatershed, respectively (fig. 2.1a). However, by 1999 due to increased urbanization, the forest, urban, and pasture areas occupied 30%, 50%, and 20% areas, respectively (fig. 2.1b). Notice that HRU-3 was initially a pasture HRU and is now a combination of 20% pasture and 10% urban. As a result, the HRU_FR variable for HRU-1, HRU-2, and HRU-3 is updated from 0.3, 0.4, and 0.3 to 0.3, 0.5, and 0.2, respectively. The constraint set for this redistribution is that the sum of HRU_FR for a subwatershed should be equal to 1. The LUC module in SWAT 2009 can be used to update such land cover changes multiple times during the model run depending on the availability of land use geospatial data. To activate the LUC module in this scenario, the model needs two files in the TxtInOut folder: lup.dat and a user-defined HRU fraction text file (say, file1.dat). Syntaxes for these files are available in the SWAT 2009 input/output documentation (Neitsch et al., 2009). Essentially, the lup.dat file provides the model with information about when the land use has changed, while file1.dat provides updated values of HRU_FR for each HRU for a particular year.

Understanding the geospatial processes behind the development of HRU layers by ArcSWAT

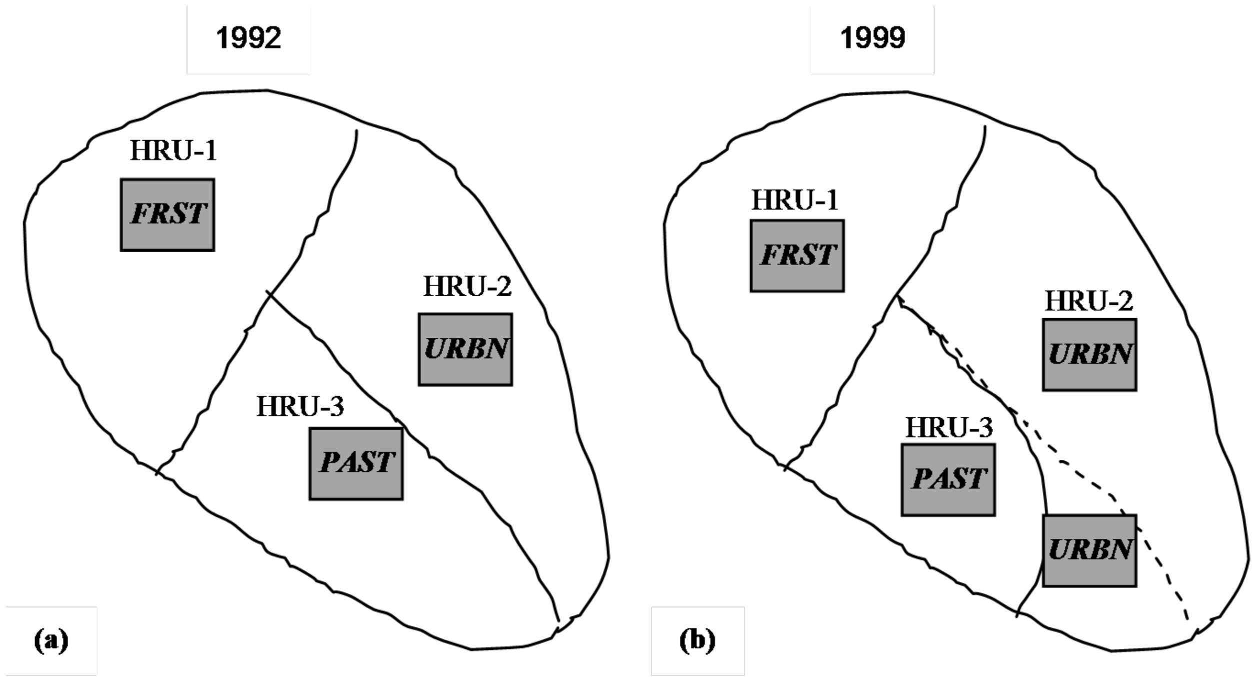

Figure 2.1: Illustration of forest (FRST), urban (URBN), and pasture (PAST) within a hypothetical subwatershed: (a) spatial distribution in 1992, and (b) spatial distribution in 1999 showing increase in urban land cover.

was important during the development of the SWAT2009_LUC tool. Once the user uploads the land use, soil, and elevation layers, ArcSWAT performs a grid-based overlay operation to identify unique combinations of land use, soil, and slope (derived from elevation) in every subwatershed. Each unique combination is then assigned an identification number (henceforth called HRU ID). Thereafter, using the HRU ID information, a thematic raster layer is created for the entire watershed that spatially identifies all HRUs. This raster layer, which is created by default in all SWAT projects, is stored in the Watershed\Grid folder of the SWAT project with filename HRU1s.aux.

If thresholds are applied to the SWAT project, due to merging, then the number of HRUs in the SWAT project is reduced compared to the situation when no thresholds are applied. Therefore, the default HRU raster (i.e., HRU1s.aux) is no longer an accurate spatial representation of the HRUs. ArcSWAT also creates a shapefile, stored in the Watershed\Shapes folder with filename hru1.shp that was primarily developed for use by visualization programs such as VizSWAT, although it is not spatially accurate (R. Srinivasan, personal communication, 9 May 2009). Currently, a geospatial layer does not exist to define accurate spatial locations of HRUs in SWAT projects with HRU thresholds.

However, spatial definition of the HRUs in raster format was a critical requirement for the SWAT2009_LUC tool algorithm. Therefore, a new approach was developed to derive a post-threshold HRU raster, which is discussed later in this article.

2.4 Materials and Methods

Depending on the size of the watershed, the resolution of input layers, and the threshold percentages applied for HRU delineation, the number of HRUs in a SWAT project can range from a few hundred to thousands. Therefore, calculating the HRU fractional area for multi-year land use geospatial datasets can be laborious and potentially a source of errors, as stated earlier. The following section describes the development of an automated tool to produce the necessary input files required to activate the LUC module in SWAT 2009.

2.4.1 SWAT2009_LUC Tool

The LUC concept described in the previous section is adapted in a user-friendly graphical user interface called SWAT2009_LUC (fig. 2.2). Three major panels (SWAT Input Data, Land Use Map Input, and Process Data) guide the user in providing the necessary input information and retrieving the output from SWAT2009_LUC. The elements within these panels such as pushbuttons, dropdowns, and form fields are sequentially enabled so that users can systematically provide the required information. The input requirement starts with the user interactively identifying the SWAT2009_LUC folder. Once this folder is identified, the tool creates three other subfolders within this folder (Shape, Raster, and Output, to store vector, grid, and output files, respectively) as the user continues to interactively provide input data to this tool. The functionality of the tool after the user identifies the SWAT2009_LUC folder is explained in the following paragraphs and illustrated in figure 2.3.

Once the SWAT2009_LUC folder is created, the user is prompted to identify the SWAT project

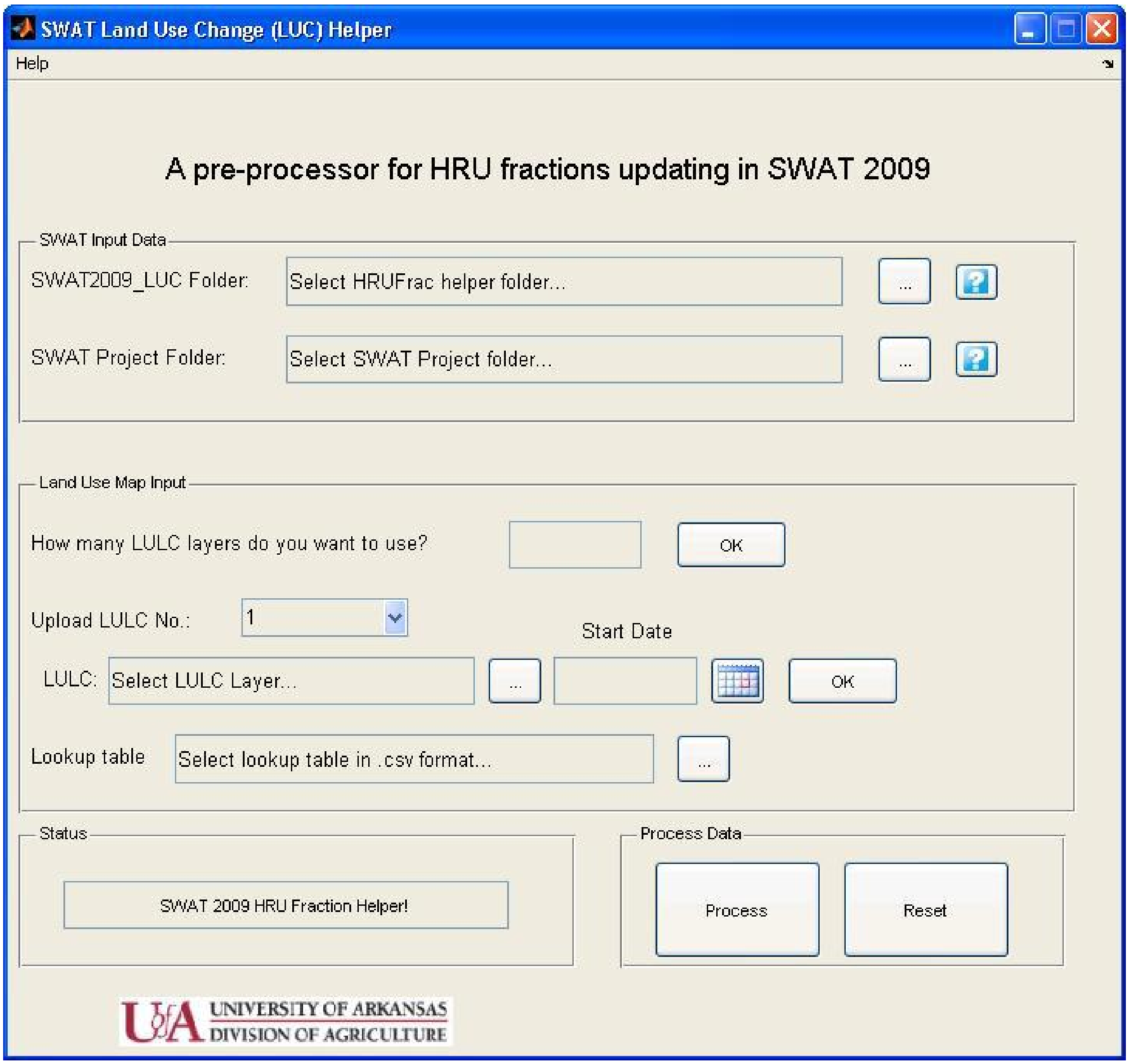

Figure 2.2: SWAT2009_LUC tool for developing input files to activate the land use change (LUC) module in SWAT 2009.

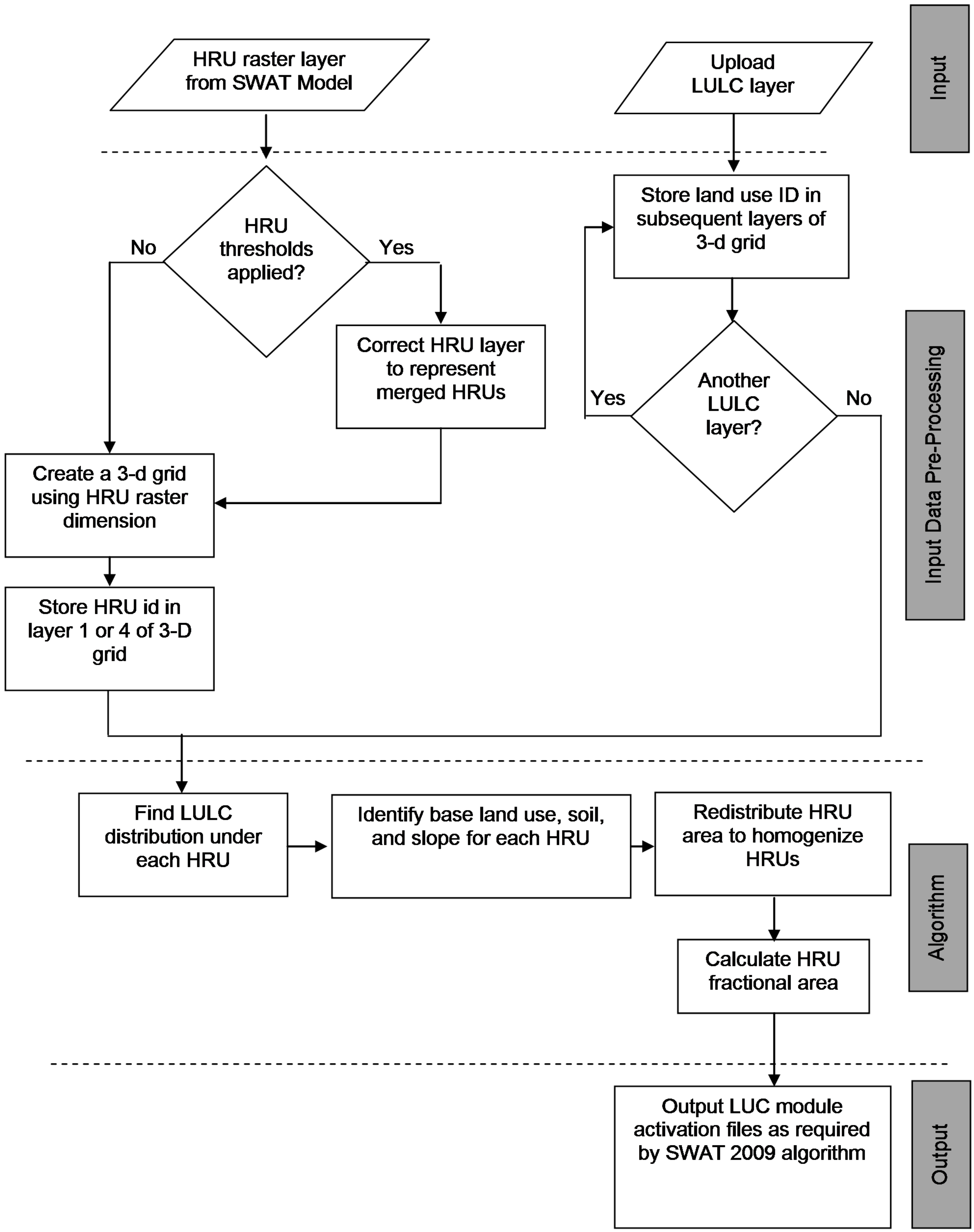

Figure 2.3: Flowchart of the SWAT2009_LUC tool for activating the land use change (LUC) module for dynamically updating land use/land cover (LULC) in SWAT 2009.

folder, following which, the tool automatically identifies the HRU raster created by ArcSWAT. Since ArcSWAT is integrated with ArcGIS (ESRI, Redlands, Cal.), the HRU layer is stored in a proprietary format. To maintain the stand-alone nature of this tool, the open-source geospatial abstraction data library (GDAL, 2010) was incorporated within SWAT2009_LUC, which allows conversion of the HRU raster to a geo-referenced tag image file format (GeoTiff). The GeoTiff format is widely used by a variety of commercial and open-source GIS software. The GeoTiff HRU is stored as layer 1 in a three-dimensional (3-D) grid whose extent is determined by the extent of the HRU layer. A similar grid-based data manipulation format was used by Pai et al. (2011) in the Field_SWAT tool to map the HRU outputs to user-defined field boundaries.

To support this grid-based operation in SWAT2009_LUC tool, a raster layer was required that identifies the spatial location of the HRUs. However, as mentioned earlier, in SWAT projects where HRU thresholds are applied, currently there exists no raster layer to spatially locate the HRUs. Therefore, an approach was developed to derive a post-threshold HRU raster using available information. ArcSWAT creates a post-threshold HRU shapefile, with filename hru1.shp, which informs SWAT2009_LUC if thresholds are applied. The attribute table of hru1.shp contains a list of the HRU IDs that actually passed the threshold. We call these HRUs the dominant HRUs. In other words, dominant HRUs are those HRUs that have passed the user-defined threshold for land use, soil, and slope within a subwatershed.

This information is used by the SWAT2009_LUC tool to spatially identify those cells within the HRU raster (HRUs1.aux) that are dominant (i.e., those that passed the threshold). The remaining HRUs are those whose land use, soil, and/or slope occupy an area within the subwatershed that is less than the thresholds provided by the user (henceforth called non-dominant HRUs). Information from hru1.shp thus allows SWAT2009_LUC to spatially separate out dominant and non-dominant HRUs in HRUs1.aux. Moreover, the information in the shapefile also allows SWAT2009_LUC to match the HRU IDs between those present in the default raster (HRUs1.aux) and those that are ultimately used in the SWAT project (hru1.shp).

In order to develop a thematic equivalence between the default raster (HRUs1.aux) and vector layer (hru1.shp) created in thresholded SWAT projects, non-dominant HRUs were merged with neighboring dominant HRUs using a Euclidean allocation method. In this method, first, a separate binary layer, with 1's and 0's representing dominant and non-dominant HRUs, respectively, was created and stored as layer 2 in the 3-D grid. Then, Euclidean distances were calculated from all dominant HRUs to nearby non-dominant HRU cells and stored in layer 3. Finally, the nearest-neighbor approach was used to merge dominant HRUs with non-dominant HRUs in HRUs1.aux.

This three-step procedure can be better explained using a hypothetical rectangular subwatershed containing 36 cells (6 rows and 6 columns), as shown in table 2.1. Table 2.1a shows the binary HRU layer for this subwatershed, which is stored as layer 2 in the 3-D grid. In this layer, the cells with value of 1 indicate dominant HRUs while those with a value of 0 indicate non-dominant HRUs. Dominant HRU cells have been highlighted in gray for better visualization. Table 2.1b indicates the minimum Euclidean distance for the subwatershed for each HRU. Euclidean distances were calculated using the following formula:

$$\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{2.1}$$

where (x_1, y_1) and (x_2, y_2) represent the coordinates of the non-dominant HRU and the nearest dominant HRU, respectively.

Table 2.1: Illustration of HRU merging based on Euclidean allocation methodology: (a) an example of binary layer with 1 representing dominant HRUs and 0 showing non-dominant HRUs, (b) Euclidean distances to the nearest dominant HRU cell, and (c) row and column numbers of the nearest dominant HRU cell.

(a) Binary HRUs						(b) Euclidean distance to nearest dominant HRU						(c) Euclidean distance allocation					
0	0	0	0	1	0	2.24	1.41	1.00	1.00	0.00	1.00	(2,3)	(2,3)	(2,3)	(1,5)	(1,5)	(1,5)
0	0	1	0	0	0	1.41	1.00	0.00	1.00	1.00	1.00	(3,2)	(3,2)	(2,3)	(2,3)	(1,5)	(3,6)
0	1	0	0	0	1	1.00	0.00	1.00	1.41	1.00	0.00	(3,2)	(3,2)	(2,3)	(2,3)	(3,6)	(3,6)
0	1	0	0	0	1	1.00	0.00	1.00	1.00	1.00	0.00	(4,2	(4,2)	(4,2)	(5,4)	(5,5)	(4,6)
0	0	1	1	1	1	1.41	1.00	0.00	0.00	0.00	0.00	(4,2)	(4,2)	(5,3)	(5,4)	(5,5)	(5,6)
0	0	0	1	0	0	2.24	1.41	1.00	0.00	1.00	1.00	(4,2)	(5,3)	(5,3)	(6,4)	(5,5)	(5,6)

As a result, notice that the dominant HRUs are assigned a value of 0.00, while the other cells are denoted with a value of 1.00, 1.41, or 2.24 units depending on the distance to the nearest dominant HRU. Using this information, each non-dominant HRU cell is allocated to the nearest dominant HRU cell, as indicated by the row and column numbers in table 2.1c. This concept was applied to HRUs1.aux to derive a post-threshold HRU layer using a matrix-based operation within MATLAB.

The derived HRU layer consists of exactly the same number of HRUs used by the SWAT model; however, more importantly, it provides a spatial definition for all HRUs, which was critical for use in SWAT projects with HRU thresholds. To validate this method, the estimated areas occupied by HRUs within a subwatershed using this method were manually compared with those calculated by ArcSWAT that are printed in the "hru" table within its project database. Once the HRU layer is developed and stored in layer 4 of the 3-D grid of SWAT2009_LUC, the requirements for the SWAT Input Data panel are complete.

Subsequently, the Land Use Map Input data panel can be used to upload multiple land use geospatial datasets. The tool assumes that all GIS layers uploaded are geo-referenced and in the same projection system as the HRU layer. Checks have been incorporated into the tool to warn users of inconsistent land use geospatial datasets. Nevertheless, users are encouraged to geo-reference land use datasets and ensure that their extents match spatially with the HRU layer created by ArcSWAT. Once proper land use geospatial datasets are uploaded, the tool converts ESRI-based formats to geo-tiff formats using GDAL. This completes the input requirement of SWAT2009_LUC, after which the user can press the Process button.

The algorithm then spatially identifies the cells for each HRU and extracts the corresponding land use data for those cells. In addition, it reads all the HRU text files in the TxtInOut folder of the SWAT project to extract the base land use, soil, and slope definition of each HRU. Because of land use change, it is likely that HRUs will not remain homogenous during the model run, as demonstrated in figure 2.1. In other words, for instance, a pasture HRU may have several cells classified as various other land uses in the subwatershed. The algorithm searches for other similar HRUs to distribute the non-homogenous cells. For instance, if the pasture HRU mentioned earlier has few cells containing urban area, the algorithm will search for urban HRUs with similar characteristics within the same subwatershed. If an HRU with the same land use and soil is not identified, then the algorithm looks for a HRU match with the same land use. Once a suitable match is identified, the non-homogenous cells are allocated to this HRU. This logical distribution is done to maintain the homogeneity of HRUs while making sure that the fractional HRUs within a subwatershed are equal to 1. The fractional area is re-calculated for each land use layer and printed in the Output folder as per the LUC module format requirements. The tool also makes a copy of the lup.dat and land use update files (one for each land use layer) in the TxtInOut folder of the SWAT project, which activates the LUC module in SWAT 2009.

In some cases, a suitable HRU may not be found to receive non-homogenous cells. For instance, if some of the pastures were converted to urban areas in a non-urban subwatershed, then SWAT2009_LUC will not be able to find a suitable HRU match within that subwatershed. Consequently, the model will continue to simulate with the existing land use for that particular HRU. This limitation is inherent in the current SWAT model framework: the model does not allow any new land uses to be introduced after initial delineation. Overcoming this limitation will probably require SWAT code modifications to introduce new land uses (or HRUs) based on temporal land use information. SWAT code modifications were outside of the scope of this work but will be addressed in future enhancements to SWAT2009_LUC.

2.4.2 Case Study: Illinois River Drainage Area in Arkansas (IRDAA)

Although the tool is applicable to any watershed, its application is demonstrated for a SWAT model developed for an urbanizing watershed in the Illinois River drainage area in Arkansas (IRDAA; 1963 km^2; fig. 2.4). A detailed discussion of the study area, SWAT model setup, and input data layers has been reported previously (Saraswat et al., 2010; Saraswat and Pai, 2011). In this article, only relevant aspects of the model setup are discussed.

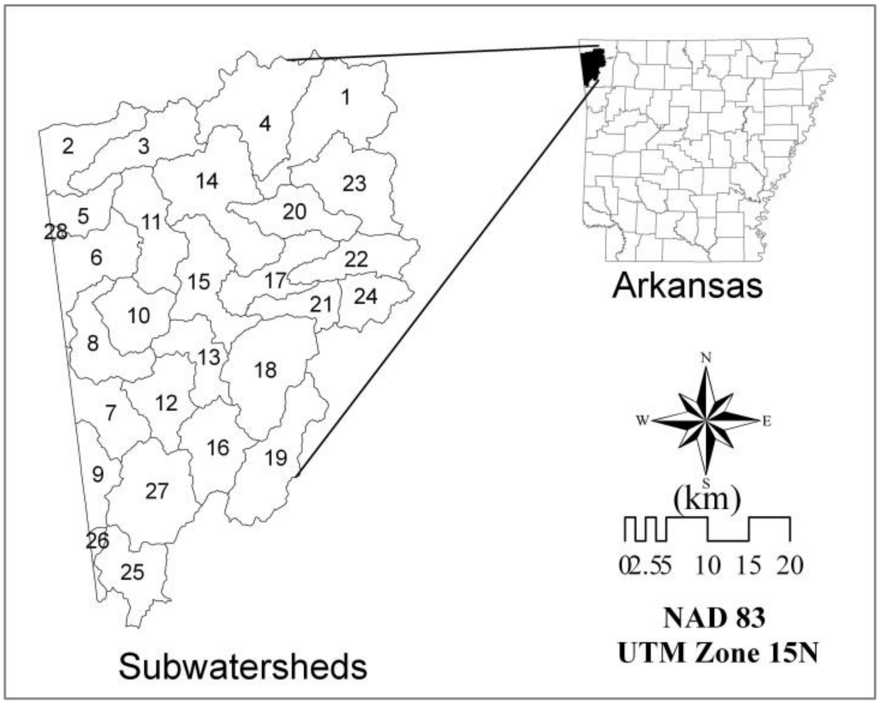

Figure 2.4: Location of the watershed and subwatershed boundaries of the Illinois River Drainage Area in Arkansas (IRDAA).

2.4.3 SWAT Model Setup

The model was set up using the ArcSWAT 2009.93.1 interface with the SWAT 2009 (version 427) algorithm. The watershed and subwatersheds were delineated using 8- and 12-digit hydrologic unit code (HUC) boundaries, respectively. Subwatershed 28 in the 12-digit HUC boundary layer has a small area ($<$0.1%) and hence was excluded from further analysis. Topography and soils data were introduced into the model using a 10 m digital elevation model (DEM) and soil survey geographic (SSURGO; USDA-NRCS, 2005) datasets, respectively, while the land use layer from the year 2006 was used to delineate initial HRUs in the model. This resulted in 8,051 HRUs, which were further merged using arbitrary thresholds of 5%, 10%, and 0% for land use, soil, and slope classes, respectively. Merging of HRUs resulted in 1,126 HRUs in the SWAT project. Precipitation and temperature during the study period (1997-2008) were acquired using a combination of NEXRAD and gauge station data, depending on their availability. These datasets were made compatible with the SWAT model using a post-processing geo-statistical tool developed by Zhang and Srinivasan

(2010). All other SWAT inputs were kept at their default values.

Land use changes in the past decade have been dynamic in the northwest Arkansas region (White and Chaubey, 2005) and in this watershed (Haggard, 2010). Hence, three land use geospatial datasets from 1999, 2004, and 2006 were used to update the initial 2006 land use distribution of HRUs using the LUC module. The land use distribution at the watershed scale generally showed increasing urban areas and decreasing pastures and forest areas from 1999 to 2006 (table 2.2).

Table 2.2: Distribution of major land uses in the Illinois River Drainage Area in Arkansas (IRDAA) watershed.

Year	Pastures (%)	Forest (%)	Urban (%)
1999	56	36	7
2004	49	37	12
2006	45	37	13

2.4.4 Evaluation Procedure

Due to the localized nature of economic growth, LUC is not uniform for all subwatersheds of the IRDAA. To understand the model response to such spatially variable land use changes, it was important to evaluate hydrological outputs at the subwatershed scale. The evaluation procedure for this study was two pronged. First, it was verified that the tool produced accurate input files for activating the land use change module. To ensure the accuracy of input files, first, the sum of the fractional area of all HRUs within a subwatershed was confirmed to be equal to 1. This requirement conforms to the basic definition of the HRU_FR variable, as discussed earlier. In addition, it was also confirmed separately whether the land use distribution produced by the input files was consistent with the land use layer supplied by the user. This was done manually by aggregating the HRU areas for each land use on a subwatershed basis and comparing it with the input LULC layer. To verify the functionality of the output files, a test was performed to determine if the input files produced by SWAT2009_LUC activated the LUC module. This was done by checking to see if the HRU areas were dynamically changing in the HRU output file (output.hru).

The second part of the evaluation consisted of verifying model sensitivity to this module by comparing model hydrological responses with and without the LUC module during the study period (1997-2008). The scope of this evaluation was limited to hydrologic processes in SWAT; water quality outputs was not considered at this time, but will be addressed in the future. Evapotranspiration, surface runoff, and groundwater are among the most dominant hydrological processes in the IRDAA (Green and Haggard, 2001). Model responses for these processes were evaluated with the LUC module turned on and off. The objective was to check the sensitivity of the module for these processes.

2.5 Results and Discussion

SWAT2009_LUC was developed in the MATLAB (The Mathworks Inc., Natick, Mass.) programming environment and is a stand-alone tool, which implies that it does not require any other GIS software on the computer. The tool was utilized to create LUC module input files for the IRDAA watershed consisting of 1,126 HRUs, which were delineated using the 2006 land use layer. Three land use geospatial datasets from 1999, 2004, and 2006 were input into the tool, with land use updates arbitrarily scheduled for January 1 of each year. As mentioned earlier, the tool organizes HRU and land use information into a grid format. The size of the grid used was 7,040 rows and 4,630 columns. Note that the grid size is a function of the original HRU layer created by ArcSWAT, which in turn is a function of the DEM layer that is read into the project.

The strength of MATLAB in processing large matrices was leveraged for this application. With all the necessary input layers and information fed into SWAT2009_LUC, the processing time for the three land use geospatial datasets was about 5 min on a desktop computer with 64-bit processor and 8 GB of RAM. This reflects a tremendous savings in time for a modeler, who may otherwise have to spend considerable time manually calculating the HRU fractional area for land use updates. Subsequently, the interface automatically copied the required files (lup.dat, file1.dat, file2.dat, and file3.dat) to the TxtInOut folder of the SWAT model, which activated the LUC module.

Because thresholds were used while developing the SWAT model, the original HRU raster developed by ArcSWAT does not accurately identify the new HRU locations. As such, the tool used a Euclidean distance allocation method to merge dominant HRUs in the original HRU raster with non-dominant HRUs. The fractional area of all HRUs within the subwatershed was equal to 1, which conforms to the definition of the HRU_FR variable. The areas of 1,126 HRUs in the newly developed HRU raster matched closely (R^2 = 0.98) to the HRU areas output by ArcSWAT (fig. 2.5). Efforts will be made in the future to enhance our algorithm so that this correlation can be improved. In addition, it was verified that the HRU area dynamically changed on January 1 of 1999, 2004, and 2006 upon scrutiny of the HRU output file (output.hru).

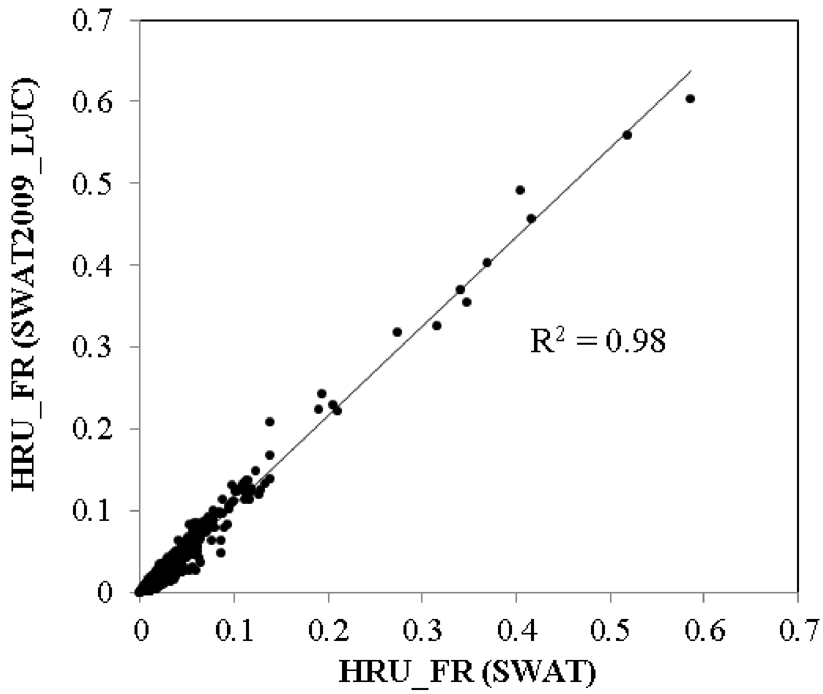

Figure 2.5: Relationship between HRU fractional area (HRU_FR) calculated by ArcSWAT and SWAT2009_LUC.

The land use redistribution produced because of changing HRU area closely matched the land use distribution in the LULC layer for all years. The results for the 1999 LULC layer are presented in figure 2.6. In this cluster bar plot, urban, forest, and pasture land use distribution from the 1999 LULC (solid border) are stacked for each subwatershed and compared with those estimated by the SWAT2009_LUC (dotted border). It is clear from the figure that land use distributions closely followed and reflected the land use from 1999. The minor discrepancies observed could have resulted because of the merging effect of HRUs. The actual land use distribution input to the

SWAT model is always slightly different from the input land use distribution (Bosch et al., 2004). Nonetheless, the LUC module input files produced by the tool were found to be reasonably true to their input land use geospatial datasets.

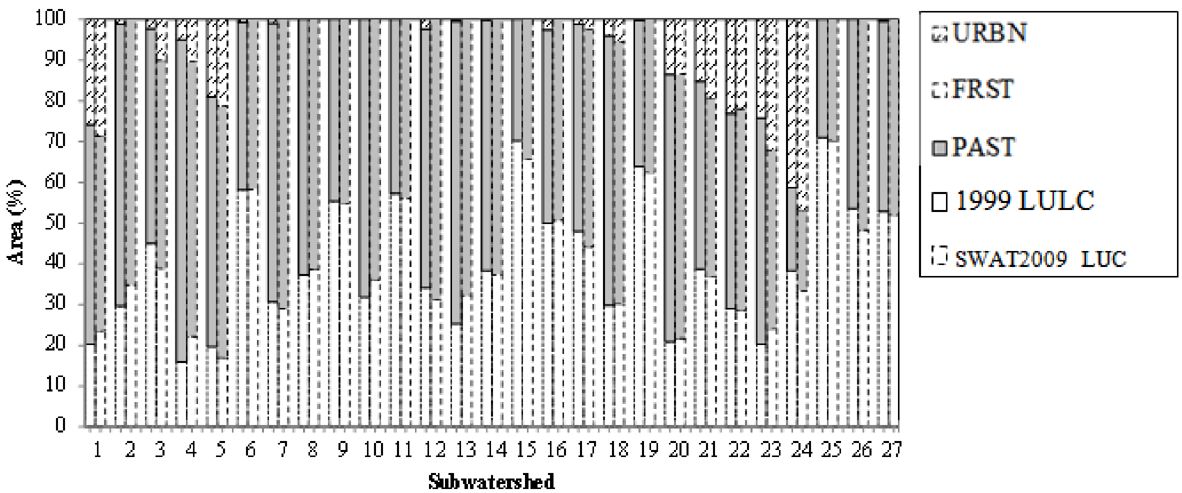

Figure 2.6: Pairwise subwatershed comparison of land use distribution estimated by SWAT2009_LUC tool (dotted border) against 1999 land use layer data (solid border). Left columns indicate land use distribution from 1999 land use, while right columns indicate those estimated by SWAT2009_LUC.

The next phase of evaluation was to understand the usefulness of the LUC module for simulating dominant hydrological processes in the IRDAA. The research question was: Are the model responses sensitive to the activation of the LUC module? To evaluate this, the model was run with and without the LUC module activated on a yearly time scale, and its overland output file (output.sub) was used to quantify the average annual evapotranspiration (ET), surface runoff, and groundwater flow. Note that the simulations without the LUC module were a function of the 2006 land use, which is characterized by large urban developments, especially in the eastern part of the watershed (subwatersheds 21, 22, 23, and 24). To quantify the land use change, a bar plot showing differences between 1999 and 2006 for each subwatershed and three major land uses has been placed on the same x-axis to understand how land use change could have a feedback effect on hydrological processes (fig. 2.7a). Depending upon the subwatershed, urban areas increased from 2% to 22% between 1999 and 2006, while during the same period forest and pasture land uses mostly decreased, with a maximum of 18%.

Figure 2.7b shows the percentage increase or decrease in simulated annual ET, surface runoff, and groundwater flow when the LUC module was activated. Activating the LUC module resulted in a gradual changing of land use from pervious to impervious surfaces, as mentioned above. Hence, we see that once the LUC module was activated, annual average groundwater flow mainly increased, with a maximum of 15%, while surface runoff mostly decreased, with a maximum of 13%.

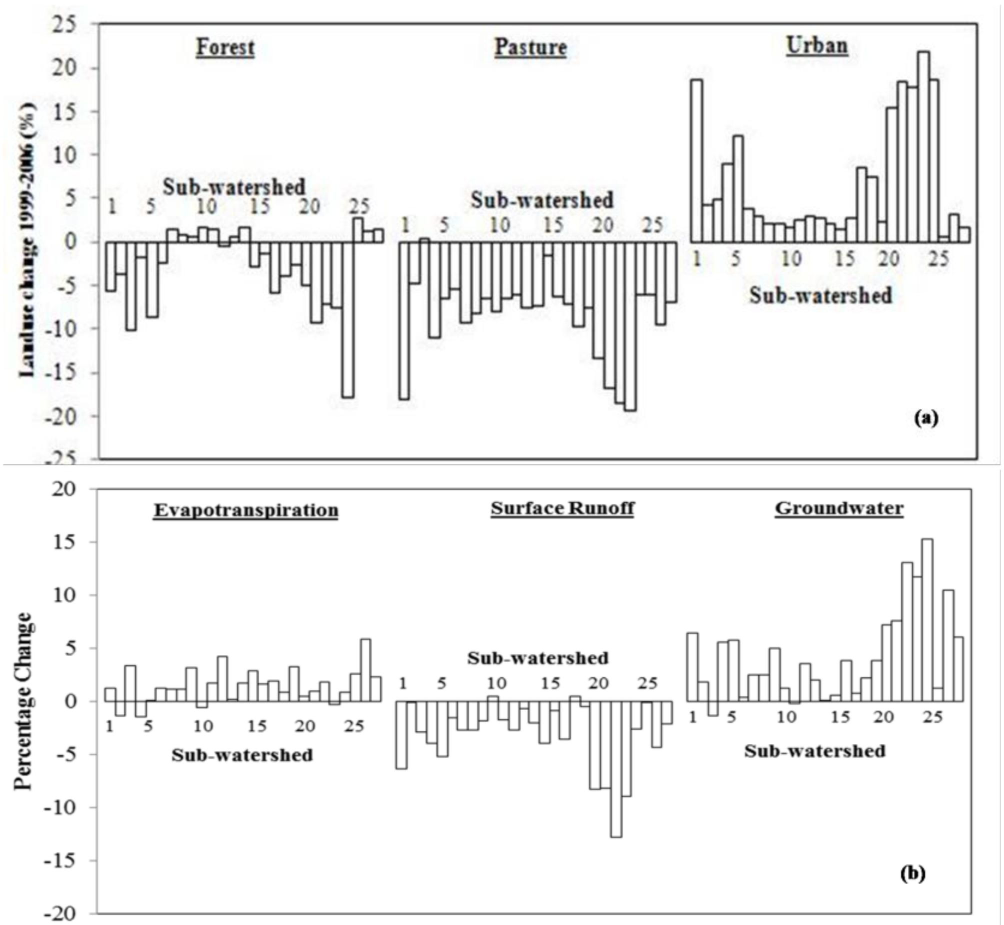

Figure 2.7: Effect of using single land use layer on key hydrological processes: (a) land use change (LUC) between 1999 and 2006 for each subwatershed, and (b) percentage change in evapotranspiration, surface runoff, and groundwater when the LUC module is activated.

Higher surface runoff and lower groundwater are typically associated with impervious areas (Tong et al., 2009). With the LUC module deactivated, the model used information from a single post-development land use layer. As a result, temporal subwatershed-scale surface runoff was overpredicted. This effect was greater for subwatersheds showing the largest increases in urban areas, where correspondingly the highest groundwater increases and evapotranspiration and surface runoff decreases were exhibited. The larger groundwater flow simulated when the LUC module was activated is perhaps a better reflection of temporal variation of land uses in the IRDAA.

In contrast, ET showed smaller changes with a general increasing trend when the LUC module was activated. ET is a combination of evaporation and transpiration. As the land cover changes from plant cover to impervious areas, transpiration is likely to decrease while evaporation is likely to increase. These two sub-processes appear to have a balancing effect in the subwatersheds of the IRDAA during the study period. Ghaffari et al. (2010) have shown that these two sub-processes can be non-linear in nature, while Li et al. (2010) showed that a threshold exists for land use to change in a watershed before ET and runoff show dramatic increases or decreases.

Regardless of the actual volume of increases or decreases in the hydrological responses, it is clear that the LUC module imparts sensitivity to the model against changing land uses in the watershed. However, as seen from figure 2.7b, this may not be spatially uniform; subwatersheds with greater urbanization exhibited greater impacts on hydrological processes. By using the SWAT2009_LUC tool and activating the LUC module in SWAT, temporal land uses can be quickly input into the SWAT model and the impact of land use changes can be better appraised. Because the model is distributed in nature, its subwatershed outputs are important not only for calibration/validation processes but also to identify critical subwatersheds (Tripathi et al., 2003). Such inter-subwatershed comparisons benefit from accurate representation of their respective land use changes. Other studies have also documented the sensitivity of the SWAT model to land use input (Heathman et al., 2009). Hence, improved spatially distributed model responses can be expected from using the SWAT2009_LUC tool.

One of the questions that may arise from this study is: Does the predictive ability of the model improve when the LUC module is activated? From figure 2.7b, it is obvious that the model sensitivity to LUC module activation is not spatially uniform. The benefits of using the LUC module are dependent on the intensity and scale of land use changes. SWAT models that are calibrated at a single-gauge in a watershed with little land use change may not exhibit the benefit of such improved spatially distributed responses. Other researchers have observed that small errors in impervious land surfaces could have a substantial effect on the uncertainty of runoff modeling results (Stuede and Johnson, 1990; Endreny et al., 2003; White and Chaubey, 2005). The findings from this study showed that in subwatersheds with greater land use changes (such as in subwatersheds 22, 23, and 24), an average of 13% higher groundwater and 8% lower surface runoff contribution was simulated when the LUC module was activated. This is likely to improve the temporal predictive ability of the model since it is a function of land use changes. However, we did not have a long-term measured dataset from either of these urbanizing subwatersheds to verify if the activation of the LUC module resulted in better predictions. Overall, based on the land use change pattern, we speculate that model responses better reflect land use changes when the LUC module is activated. Nevertheless, availability of a measured long-term dataset from an urbanizing area is expected to further improve our understanding of the LUC module in SWAT.

2.6 Summary

The results from this article advance SWAT model applications in two ways. First, they provide SWAT modelers with a novel computer-based geospatial tool, SWAT2009_LUC, to prepare input files required to activate the LUC module in SWAT 2009. Results from application to the IRDAA SWAT model showed that the tool was able to produce LUC module input files that successfully and accurately changed the land use three times during the model run period. Once the tool ingests the necessary input datasets and information, the time required for development of these files was only about 5 min. Because the LUC module input is data intensive, this tool can encourage modelers to quickly verify if incorporating land use changes enhances their models' predictive abilities.

Secondly, the results provide theoretically underpinning and demonstrate advantages of the new LUC module in SWAT 2009. Model responses were studied with and without the LUC module activated for the urbanizing IRDAA watershed. Depending on the subwatershed, the urban areas increased by 2% to 22% during the study period, which resulted in overprediction of groundwater by up to 15% when the LUC model was not activated. In addition, a single post-development LULC layer overpredicted the surface runoff for most subwatersheds. In summary, activation of the LUC module is expected to result in improved temporal and spatial hydrological responses at the subwatershed scale.

Acknowledgements

This project was made possible due to financial support from the Arkansas Natural Resources Commission (ANRC) through the 319(h) funding program. Dr. Raghavan Srinivasan at Texas A&M University answered many questions related to HRU delineation in ArcSWAT. Part of this research stemmed from e-mail communications with Dr. Jeff Arnold, Ms. Nancy Sammons, and Dr. Mike White, who patiently explained the workings of the LUC module in SWAT 2009. We thank three anonymous reviewers and the ASABE Associate Editor for their efforts in improving the manuscript.

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Chapter 3

Identifying Priority Subwatersheds in the Illinois River Drainage Area in Arkansas Watershed Using a Distributed Modeling Approach

3.1 Abstract

This article describes a modeling approach for prioritizing 12-digit hydrologic unit code subwatersheds in the Illinois River Drainage Area in Arkansas (IRDAA) watershed utilizing the soil and water assessment tool (SWAT) model output for sediment, total phosphorus (TP), and nitrate-nitrogen (NO_3-N). The model was calibrated and validated at seven locations for total flow, base flow, and surface runoff and at three locations for water quality outputs. A multi-objective function consisting of percent relative error (RE), Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), coefficient of determination (R^2), and ratio of the root mean square error to the standard deviation of measured data (RSR) was used to guide model evaluations. The resulting priority subwatersheds comprised only 24% of the total area of the watershed but contributed 49% of sediment, 33% of TP, and 27% of NO_3-N simulated loadings. Statistical relationships between priority subwatersheds and their various characteristics assisted with supporting the prioritization results. For the IRDAA, this approach produced results that could assist watershed management agencies in optimizing allocation of limited resources in addressing water quality issues.

Keywords. *Erosion, Modeling, Nutrient transport, Pollution, Prioritization, SWAT, Watershed.*

3.2 Introduction

The Arkansas Department of Environmental Quality (ADEQ) has reported that 37% of the assessed waters in Arkansas are impaired for at least one designated use (ADEQ, 2008). Determining the exact cause of impairments and delineating the geospatial range of landscapes within an 8-digit watershed that need corrective action to provide effective protection and rehabilitation in an economically feasible manner is difficult with limited resources and information. An alternative is to target smaller areas or subwatersheds that contribute disproportionately to the overall pollutant load. Identification of such target areas in the research literature have been described using various terminologies such as hot spots, critical source areas (White et al., 2009), and variable source area (Frankenberger et al., 1999). The difficulty of this approach lies in determining reliable cause-and-effect relationships for each subwatershed and using that information to prioritize each subwatershed's influence on the overall watershed. A simulation approach that can effectively accomplish this could provide a relatively low-cost tool to help watershed protection and rehabilitation efforts.

Subwatershed prioritization, in the past, was accomplished using known land resources and water quality issues (Duda and Johnson, 1985; Maas et al., 1985). However, Tim et al. (1992) used separate models to determine soil erosion rates, sediment yield, and phosphorous loading in the Nomini Creek watershed, Virginia, and identified areas with low, medium, or high nonpoint-source pollution potential. Other researchers have used data derived from remotely sensed data, such as slope, drainage density, aspect, forest cover, and soil type as parameters for subwatershed prioritization (Karale et al., 1977; Khare et al., 2007). Dickinson et al. (1990) used the empirical Guelph model for evaluating the effects of agricultural management systems on erosion and sedimentation (GAMES) to identify critical areas.

The focus of this study is to develop a simulation approach for prioritizing subwatersheds and to evaluate its performance in the Illinois River Drainage Area (IRDAA) watershed in northwest Arkansas where long-term water quality monitoring and input data exist. It also provides a "real-world setting" where urbanization has been extensive during the past 10 to 15 years and management of point and nonpoint sources of pollution has undergone change, as reported in detail by Haggard (2010) and Sharpley et al. (2009). The modeling requirements included setting up a multi-site calibrated watershed model that integrates changing management practices in the IRDAA and leverages the large amount of spatially distributed data. Therefore, the overarching constraint was that the model setup and prioritization methodology should incorporate all sources of pollution based on the best available information.

Reviews of previous model applications and model intercomparison studies (Borah and Bera, 2004; Gassman et al., 2007; Douglas-Mankin et al., 2010; Nejadhashemi et al., 2011) were helpful in identifying an appropriate model for this task. Borah and Bera (2004) reviewed eleven watershed models and concluded that the hydrological simulation program - Fortran (HSPF) and SWAT were suitable for predicting yearly flow volumes, sediment, and nutrient loads. Nejadhashemi et al. (2011) evaluated the spreadsheet tool for estimating pollutant load (STEPL), pollutant loads for watersheds (PLOAD), long-term hydrologic impact assessment (L-THIA), and soil and water assessment tool (SWAT) models for identifying pollutant priority areas in a Kansas watershed. They concluded that a calibrated SWAT model provided the least uncertain results when identifying high-priority areas within their watershed. Tolson and Shoemaker (2007) noted that SWAT took full advantage of spatially distributed input datasets compared to the lumped-parameter generalized watershed loading function (GWLF) model, which provides responses only at the outlet. Moreover, the authors observed that the SWAT model treats soil nutrient levels as state variables and therefore simulates dynamic soil nutrient levels, which was not the case in the GWLF model. The IRDAA watershed has a history of land application of manure and fertilizer (Sharpley et al., 2009; Haggard, 2010; Scott et al., 2011) and its reliable representation was critical to this modeling study. Overall, based on the literature review, it was concluded that the SWAT model provided an adequate temporal and spatial framework to satisfy the objectives of this watershed-scale modeling and prioritization study.

Typical broad steps involved in applying SWAT for subwatershed prioritization are: model setup, calibration, validation, and prioritization. The SWAT scientific literature includes many guidelines for setup, calibration process (e.g., Santhi et al., 2001), and statistical and graphical evaluation of model results (e.g., Moriasi et al., 2007). Among the studies that report model calibrations, only a handful report use of multiple-site data and concur that such an approach accounts for better simulation of hydrologic patterns in the subwatersheds compared to using single-site data (Santhi et al., 2001; Qi and Grunwald, 2005; White and Chaubey, 2005; Saraswat and Pai, 2011). Annual and monthly scale SWAT outputs have been used extensively to support various water management objectives (Jayakrishnan et al., 2005; Santhi et al., 2006; Douglas-Mankin et al., 2010). However, it was found that fewer studies have actually focused on examining SWAT model results to prioritize subwatersheds.

Tripathi et al. (2003) used the SWAT model's annual overland output for subwatershed prioritization. While their methodology was consistent with their modeling goals, its applicability is limited in a watershed with substantial fluvial and point-source pollutant contributions. Point-source impacts from wastewater treatment plants (WWTPs) and nutrient contribution from benthic sediment are a significant source of alteration in stream nutrient cycling in the IRDAA (Haggard et al., 2005; Ekka et al., 2006; Haggard et al., 2007; Haggard, 2010). However, these sources are not factored into the prioritization methodology of Tripathi et al. (2003).

The problem of prioritization is further compounded due to spatial interaction of subwatersheds. Using reach output from models can potentially result in downstream subwatersheds having a greater chance of appearing high on the priority list due to load accumulation. For instance, consider the study conducted by Kalin and Hantush (2009) for the Pocono Creek watershed, Pennsylvania, for prioritization. Their objective was to evaluate the role of subwatershed subdivision scale for identifying critical subwatersheds for flow responses. The effect of spatial interaction was clearly seen in the priority maps; in fact, the authors noted that geographic proximity of a subwatershed to the watershed outlet played a critical role in their methodology. From a subwatershed prioritization and management perspective, this situation is not ideal. The ultimate goal is to use subwatershed responses that represent individual contributions from current and past management activities and not because of a subwatershed's spatial location in the watershed. Saghafian and Khosroshahi (2005) concluded that a successful prioritization project must look beyond analyzing the impaired areas by studying the contribution of headwater subwatersheds. The bias seen by Kalin and Hantush (2009) due to geographic proximity to the watershed outlet indicates the need for careful evaluation of current prioritization methods.

One of the challenges faced in a prioritization project is that measured data are typically not available at all subwatershed outlets for quantitatively validating the results. Previous SWAT studies have not attempted to validate prioritized subwatersheds due to lack of spatially explicit data (Tripathi et al., 2003; Kalin and Hantush, 2009). Watershed managers and stakeholders may remain unconvinced with model-generated priority subwatersheds because the model has not been validated at all subwatershed outlets. Refsgaard (2001) stressed that modelers need to make better use of additional information for validation that will help strengthen the confidence in distributed model outputs at internal locations. Therefore, a surrogate method is required that can validate the output when monitoring data are unavailable. Landscape characteristics such as land use, soil hydrologic group, and slope were used by Ghebremichael et al. (2010) to explore the characteristics of model-generated critical source areas at the hydrological response unit (HRU) scale. However, SWAT was designed to make predictions at the watershed and subwatershed scale at which routing is simulated, not at the HRU scale, which does not have spatial definition within the model (White et al., 2009). In fact, long-term water quality data are typically available at the subwatershed scale, which is used to calibrate and validate the SWAT model. For instance, in the IRDAA watershed, flow measurements are available for seven subwatersheds, while long-term and high-frequency water quality data are available at the outlet of three subwatersheds. For non-calibrated subwatershed outlets, previous studies known to us have not attempted to verify model responses through surrogate means.

Water quality issues identified from monitoring projects can also complement a model-generated priority list. In the IRDAA watershed, several known water quality impairments exist, as reported in the 303(d) list of impaired waterbodies (ADEQ, 2008). The 303(d) list is an outcome of extensive and long-term water quality monitoring. It is critical to consolidate information from various sources to substantiate model-generated results. However, no prioritization study has attempted to link the priority subwatersheds with key subwatershed metrics and known impairments. Such linkages between subwatershed characteristics and priorities not only serve to qualitatively validate the results from SWAT but also increase the confidence of watershed managers in accepting model-based subwatershed priorities.

Our overall goal in this study was to examine the applicability of SWAT model output for the purpose of subwatershed prioritization in a watershed affected by point and nonpoint sources of pollution. Specific objectives were to: (1) develop the SWAT model for the IRDAA watershed; (2) calibrate its output for total flow, surface flow, base flow, sediments, total phosphorous (TP), and nitrate-nitrogen (NO_3-N) using multi-site data; (3) develop an approach for subwatershed prioritization that incorporates both point and nonpoint sources of pollution and is not affected by the spatial locations of subwatersheds; and (4) qualitatively validate the prioritization approach using various subwatershed metrics and known water quality impairments.

3.3 Materials and Methods

3.3.1 Study Watershed Description

The study was conducted in the IRDAA watershed, a part of the Illinois River watershed (IRW) with a drainage area of approximately 1960 km^2. The watershed is located in northwest Arkansas and covers portions of Benton (39.5%), Crawford (0.2%), and Washington (60.3%) counties (fig. 3.1). The climate in the region is humid continental with average annual precipitation of 1164 mm. The topography of the watershed can be characterized by moderately rolling hills due to the presence of the Ozark and Boston Mountains. The population in Benton and Washington counties has increased by 47.1% and 26.9%, respectively, during 2000-2009 (U.S. Census Bureau, 2010). The watershed is also characterized by increased residential, commercial, and infrastructure construction activities, all of which together may increase strain on natural resources. The watershed is home to a number of animal enterprises, including poultry, swine, and cows (beef and dairy).

The IRDAA has been a subject of study by various agencies (Parker et al., 1996) that have attributed water quality impairments to point and nonpoint sources (Green and Haggard, 2001). The ADEQ's 2008 Section 303(d) list of impaired waterbodies has identified sections of the Illinois River and a few tributaries as being impaired for designated uses (ADEQ, 2008). The leading causes for inclusion of river segments and creeks in the 303(d) list for the IRDAA are siltation/-turbidity, pathogens, TP, and NO_3-N from point and nonpoint sources, while the major designated

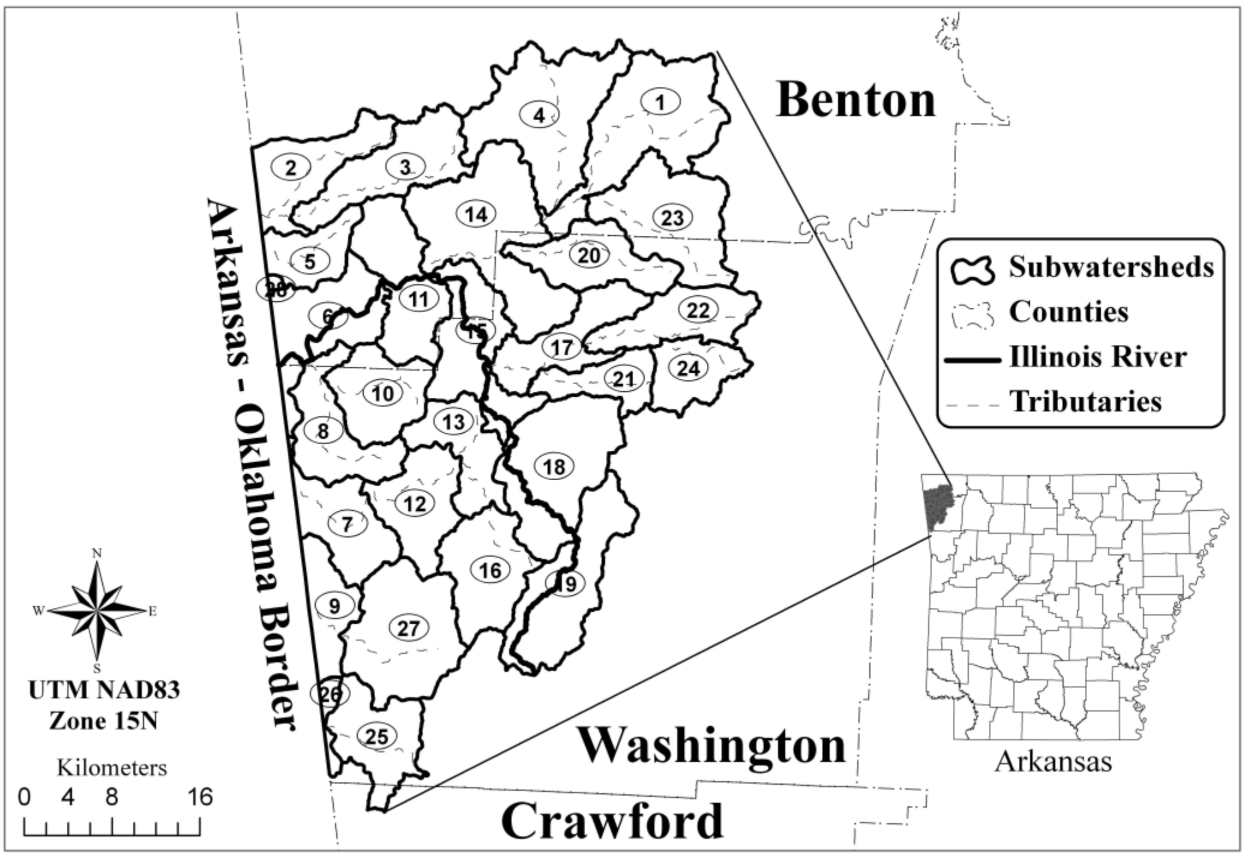

Figure 3.1: Location of Illinois River Drainage Area in Arkansas (IRDAA) watershed.

uses that have been impaired are aquatic life and primary contact. In order to effectively manage the pollutant sources, the ANRC plans to encourage implementation of rehabilitation efforts at the subwatershed scale. A SWAT model was developed to help the ANRC identify subwatersheds that can be targeted for this purpose. The following sections provide relevant background on SWAT and its setup for the IRDAA.

3.3.2 SWAT Model Description

SWAT is a watershed-scale, physically based hydrological model developed by the USDA Agricultural Research Service (ARS) (Gassman et al., 2007). The model simulates on a daily time step and predicts impact of management practices on water, sediment, and nutrient outputs in large watersheds having point-source and nonpoint-source inputs over a long period (Santhi et al., 2001). An extensive body of literature exists on the hydrological and pollutant fate and water quality processes simulated by the SWAT model (Gassman et al., 2007). Since the focus of this study is the application of the distributed model results for priority subwatershed identification, only the SWAT components related to model structure and outputs are briefly reviewed.

The model requires several watershed-specific input datasets that are typically available in the form of geographical information system (GIS) layers. To facilitate the processing of these layers, ArcSWAT (Winchell et al., 2008), a freely available ArcGIS (ESRI, Redlands, Cal.) extension, can be downloaded from the SWAT website (http://swatmodel.tamu.edu). ArcSWAT first divides the watershed into subwatersheds. Subwatersheds are areas within the watershed that are hydrologically connected. Subsequently, the subwatersheds are divided into fragmented areas of land known as hydrologic response units (HRUs), which are essentially homogenous areas of land cover, soil, and slope within a subwatershed. This division of a watershed into subwatersheds and further into HRUs allows representation of the watershed's heterogeneity. Management operations, such as cropping practices including planting, agrochemical applications, harvesting, and irrigations, and many structural or nonstructural best management practices may be simulated for each HRU separately.

Water and pollutant loadings from all HRUs within a subwatershed are aggregated on a daily basis since HRUs are assumed to have no spatial interaction. At this point, the modeler has the choice to turn on or off the QUAL2E in-stream equations using ArcSWAT. If the QUAL2E equations are turned on, the model routes the loading from the HRUs and point sources, if any, through the main channel of the subwatershed, during which the loading may undergo processes such as deposition, settling, channel losses, algal uptake, etc. If the option is turned off, the model considers the aggregated output from the HRUs and point sources as the output of the subwatershed. In either case, the subwatershed output is input to the immediate downstream subwatershed. This continues from the headwater subwatersheds to the watershed outlet.

Responses can be printed for each HRU and subwatershed separately on a daily, monthly, or annual basis. A modeler may use the appropriate subwatershed output to compare with data from monitoring stations either manually or automatically and adjust input parameter values in a logical way to more closely simulate watershed conditions and better predict measured data. This process is known as model calibration. Automatic calibration methods have been developed for the SWAT model that use probabilistic, Bayesian, and genetic algorithm-based approaches.

3.3.3 Input Data Description

3.3.3.1 DEM

The topography of the IRDAA watershed was defined using a GIS-based resampled digital elevation model (DEM) layer at 10 m spatial resolution obtained from the Center for Advanced Spatial Technology at the University of Arkansas in Fayetteville. Other research studies have shown that even a 30 m resolution DEM produces adequate simulations from SWAT (Cotter et al., 2003; Chaubey et al., 2005). The mean elevation in the watershed is about 379 m and ranges from 272 to 598 m. The majority of the watershed area (71.9%) is under 3% to 8% slopes and >8% slopes, which is typical of the irregular topography in the Ozark Highlands eco-region.

3.3.3.2 Subwatershed and HRU Delineation

Two options are available within SWAT to divide a watershed into subwatersheds: DEM-based or user-defined. In the present study, a user-defined approach was adopted to generate subwatershed boundaries that matched the 12-digit hydrological unit code (HUC) boundaries defined by the U.S. Geological Survey (USGS). The geomorphologic resolution of subwatersheds has been reported to affect SWAT sediment and nutrient outputs (Bingner et al., 1997; Mamillapalli, 1998; FitzHugh and MacKay, 2000; Jha et al., 2004; Arabi et al., 2006). Therefore, our approach to align the subwatershed boundaries with pre-defined 12-digit HUC boundaries was primarily to ensure reproducibility of the model structure and outputs. Additionally, it also met requirements of the ANRC to encourage conservation practices at this scale.

The subwatershed delineation was followed by creation of HRUs. We used thresholds of 5%, 10%, and 0% for land cover, soil, and slope, respectively. Subsequently, the model created HRUs using all unique combinations of soil, land cover, and slope in each subwatershed. Non-dominant HRUs (those occupying less than threshold percentage) created by ArcSWAT were then merged with dominant HRUs using a GIS overlay process (Pai et al., 2011). Based on this delineation, the SWAT model created 848 HRUs for the entire watershed. It may be noted that there is no universally accepted guideline for HRU delineation thresholds. Higher computational power is required at lower thresholds because of the greater number of delineated HRUs. Hence, a compromise between computational cost and adequate representation of spatial variability is recommended (Gitau, 2003).

3.3.3.3 Land Use Change

Land use in the IRDAA watershed has changed from pasture to urban and forested areas in recent years (Haggard, 2010). The impact of land use changes on watershed hydrology (Fohrer et al., 2002; Fohrer et al., 2005; Krysanova et al., 2005; Lorz et al., 2007), nutrient, and sediment loss prediction (Lenhart et al., 2003) has been previously reported. Using a single land use layer limits the model's ability to simulate the water quality impacts of temporal land use changes. In fact, Chiang et al. (2010) reported that the benefits of any conservation practice could be masked by simultaneous negative effects of land use changes such as urbanization. Hence, it was critical to represent land use change in the IRDAA SWAT model.

Temporal land use maps, over the entire modeling period, were obtained from two different agencies that used different classification schemes (table 3.1). Therefore, each map was post-processed to ensure that a common land use classification was used within the model.

Table 3.1: Categories merged in LULC maps for compatibility with SWAT.

LULC Year (Agency)	Categories	Name	Merged/Used in SWAT
1992 and 2001 (NLCD)[a]	21, 22, and 85	Residential (low/high) or recreational	Urban low intensity
	23 and 24	Commercial, industrial, transportation	Urban high intensity
	41, 42, and 43	Deciduous, evergreen, and mixed	Forest
1993 (CAST[b])	1, 2, 4, 6, 8, 9, 10, 11, 12, 13, 14, 17, 18, 19, 20, 23, 24, 32, 33, 34, 36, 38, 39, 40, 41, 42, 45, 48, 51, and 52	Different tree types (pine, oak, hardwoods, etc.)	Forest
1999, 2004, and 2006 (CAST)	11 and 14	Intensity 1 and urban (other)	Urban low intensity
	12 and 13	Intensity 2 and intensity 3	Urban high intensity
	100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, and 128	Different tree types (pine, oak, hardwoods, etc.)	Forest
	209 and 210	Warm season and cool season grasses	Pasture

[a] National Land Cover Database.
[b] Center for Advanced Spatial Technology, University of Arkansas.

Subsequently, the 1992 National Land Cover Database (NLCD) dataset was used for delineating HRUs. Within the SWAT algorithm, one of the key characteristics of an HRU is its area, which is defined using the variable HRU_FR. The value of this geomorphologic variable ranges from 0 to 1 and specifies the fractional area occupied by the HRU within the subwatershed. The HRU_FR was parameterized by ArcSWAT using the 1992 land cover map to represent the percentage area of the HRU. Previous versions of SWAT treated HRU_FR as constant throughout the model simulation period, which resulted in a static land use distribution. However, in SWAT 2009, a land use change (LUC) module has been included that allows HRU_FR to be varied during model simulation (Arnold et al., 2010). Chiang et al. (2010) successfully demonstrated an application of the LUC module to separate water quality impacts resulting from land use changes and best management practice implementation. The LUC module is also well suited to allow model responses, such as runoff and pollutant transport, to respond dynamically to land use changes in the IRDAA. Hence, the LUC module was used to update the HRU land cover fractions for the 848 HRUs for each LULC year (1993, 1999, 2001, 2004, and 2006) using the SWAT2009_LUC geospatial tool (Pai and Saraswat, 2011a, 2011b).

3.3.3.4 Soil

Soil characteristics of the study area were obtained from the Soil Survey Geographic (SSURGO) soil database. SSURGO is currently the most comprehensive soil database available for Arkansas. The soils in the study area belonged to 24 different soil series, with the majority soil series being Enders (25.2%), Captina (15.5%), Nixa (15.5%), and Clarksville (11.3%). These soil series are classified into hydrologic group C, except for Clarksville, which is categorized into hydrologic group B. Soils classified into hydrologic groups B and C have moderate and low infiltration rates, respectively (USDA-SCS, 1972).

3.3.3.5 Weather

Historical daily precipitation for 13 years (1981-1993) was obtained from the National Climatic Data Center (NCDC) for three stations located at the cities of Bentonville, Fayetteville, and Gravette. An inverse distance weighted spatial interpolation method was used to obtain daily precipitation estimates at the centroid of each subwatershed using the GIS-based precipitation interpolation software developed by Zhang and Srinivasan (2010).

Improved hydrologic responses can be expected when using Next-Generation Radar (NEXRAD) precipitation data in SWAT (Di Luzio and Arnold, 2004; Moon et al., 2004; Kalin and Hantush, 2006). Hence, hourly NEXRAD data at a resolution of 4 km from 1994 to 2008 were acquired, spatially and temporally aggregated, and assigned to pseudo weather stations located at the centroid each subwatershed using a tool developed by Zhang and Srinivasan (2010). Minimum and maximum daily temperatures from the Bentonville, Fayetteville, and Gravette stations were also included in the model. Additional climatic inputs such as solar radiation, relative humidity, and wind velocity were generated by SWAT's internal weather generator. Evapotranspiration was simulated using the Penman-Monteith method, and routing was simulated using the variable storage method.

3.3.3.6 WWTP Data and Assumptions

Pollutant discharge data from eight major point-source discharges, primarily wastewater treatment plants (WWTPs), were obtained from the ADEQ and incorporated for each year separately. The frequency of data reported to ADEQ by WWTPs varied (monthly, quarterly, or biannually) based on the permit requirements. Hence, to avoid any bias, the data were aggregated and input on an annual scale into the model. During the years when data were absent, average annual values were used from the years when the data were available. The model requires the proportions of organic and inorganic phosphorus in total phosphorus. We assumed that the typical TP effluent from a WWTP included 20% organic P and 80% inorganic P (Lin et al., 2009). Information on land application of sludge was available, at best, in the form of rough estimates from a few point-source facilities; therefore, it was not considered as a model input.

The city of Fayetteville has two WWTPs: Noland and West Side. The Noland WWTP had two outfalls: 001 and 002. Outfall 001 discharges into the neighboring Beaver Lake watershed (HUC 11010001), while outfall 002, until June 2008, discharged into Mud Creek (subwatershed 24). After June 2008, the discharge into Mud Creek was discontinued. In addition, Fayetteville's West Side WWTP became operational in June 2008 and started discharging into Goose Creek (subwatershed 18). Since these two WWTPs operated for only a part of the year in 2008, their data were included as monthly estimates from 1995 to 2008 in the model. This additional step was required because SWAT can ingest either annual or monthly estimates from a point-source discharge during the study period.

The constituents of effluents reported by various point-source dischargers varied based on their permit requirements. Flow, total suspended sediments, TP, ammonia-nitrogen, pH, temperature, chemical oxygen demand, biochemical oxygen demand, and carbonaceous oxygen demand were some of the more commonly reported constituents. Other major biologically available forms of nitrogen are NO_3-N and organic nitrogen. Among all the point sources in this watershed, NO_3-N was reported only by the city of Rogers WWTP from January 1993 onward, while organic nitrogen was not reported by any of the point sources. Since identification and prioritization of subwatersheds based on NO_3-N contribution was one of the objectives of this study, it was critical to represent all sources.

In the absence of measured data, previous studies were reviewed for estimating all forms of nitrogen in point-source effluent discharge. Schilling and Wolter (2009) used either the facility's design limit (if available) or a constant nitrogen value proportional to the population estimate. In calculating these estimates, the authors assumed that 4.5 kg (9.9 lb) of nitrogen were generated per person per year and that all of this nitrogen was in the form of nitrates. Estimates from this method can be questionable because other forms of nitrogen were ignored and population estimates may include rural areas that typically have on-site septic disposal systems. The Chesapeake Bay program used available data from Virginia WWTPs to define distribution of various nitrogen forms in effluent discharge. In this approach, municipal point-source facilities were divided into three types based on treatment technologies: without nitrification, with nitrification, and with denitrification. The distribution of various nitrogen forms suggested were 80%-3%-17% (without nitrification), 7%-80%-13% (with nitrification), and 12%-73%-15% (with denitrification) for NH_4-N, NO_3-N, and organic N, respectively (Wiedeman and Cosgrove, 1998). It is clear from this distribution that the presence of either nitrification or denitrification treatment processes helps in lowering the ammonia-nitrogen but increases the nitrate-nitrogen in effluent discharge. The amount of organic-nitrogen stays approximately constant (13% to 17%). Since ammonia-nitrogen is a typically reported nitrogen form by WWTPs in Arkansas, this approach was explored for estimating other forms of nitrogen in the effluent discharge from WWTPs in the IRDAA.

Based on consultation with local experts experienced in measuring and evaluating impacts of point sources on water quality, a distribution of 4%, 75%, and 21%, for NH_4-N, NO_3-N, and organic N, respectively, for nitrogen sources in effluents from all the point sources in Arkansas was assumed (University of Arkansas Environmental Task Force Water Quality Subgroup, personal communication, 29 June 2010). Since NH_4-N loads were typically available from point sources, corresponding organic N and NO_3-N loads were estimated using the above distribution.

3.3.3.7 Management Practices

Since a majority of the study area (99.8%) is in Benton and Washington counties, management data collection pertains to these two counties only. This region is home to a number of animal enterprises, including poultry, pigs/hogs, and cows (beef and dairy). The population of cows in Benton and Washington counties has remained close to an average 109,000 over a period of ten years, with approximately equal proportion of beef and dairy. The watershed-level cow population was estimated by apportioning the county-level population figures to the pasture acreage of the watershed within each county based on the approach described by White and Chaubey (2005). The SWAT model allows representation of grazing operations in the management files through uniform removal of biomass from pasture HRUs per unit area on a daily basis (table 3.2).

The grazing rate (in the form of density) in each subwatershed was calculated as follows:

1. Assuming approximately 523 kg per cow, each cow's intake averages 10.88 kg d^{-1} while grazing on Bermuda and Tall Fescue and 10.43 kg d^{-1} when fed with hay (NAS, 1996; T. Troxel, personal communication, 23 October 2008).

2. The total daily consumption rate of grass in a subwatershed was obtained by multiplying the daily consumption rate from step 1 by the number of cows estimated in each subwatershed.

Table 3.2: Pasture management and cattle operations.

Operation	Details
Grazing operation	1 May to 30 September (Bermuda), 1 October to 30 November (Fescue), and 1 March to 30 April (Fescue). Grazing density is 12.55 and 15.31 kg grass (dry weight) ha^{-1} d^{-1} in Benton and Washington, respectively.
Manure deposition	5.99 kg ha^{-1} d^{-1}
Hay cutting	31 May and 15 July; 85% removal.

3. The daily consumption was divided by the subwatershed's pasture area to obtain the grazing density (kg d^{-1} ha^{-1}).

The average daily grazing densities for Benton and Washington counties were 12.55 and 15.31 kg ha^{-1} d^{-1}, respectively. Grazing was scheduled for 180 days, starting 1 May on Bermuda pastures, and for two 60-day grazings, starting 1 October and 1 March on Fescue pastures. Manure deposition was estimated at 4.32 kg d^{-1} (NAS, 1996) assuming 523 kg per cow, which was converted to 5.99 kg ha^{-1} d^{-1} using the methodology described previously for finding grazing density. The values of daily grazing density and manure deposition were found to be consistent with those used by Chiang et al. (2010) for a subwatershed of the IRDAA.

Manure and litter generated from poultry operations has been historically applied as fertilizer to pastures in the watershed (Haggard, 2010). The locations of land application (HRUs) were required for representing this practice in the model. A review of land application methods, for simulating litter application within hydrological models, revealed three general approaches: (1) uniform application of litter on all pasture areas (Cotter et al., 2003), (2) litter application based on the proportion of area under pasture in each county (Storm et al., 2006), and (3) litter application on pasture lands within a circular area of fixed radius around the poultry houses (Lin et al., 2009). Due to litter's low economic value, transporting poultry litter to great distances is not cost-effective

(Slaton et al., 2004). As a result, poultry litter is likely to be applied to pasture fields close to the production site (White et al., 2009). The third approach, by Lin et al. (2009), was considered appropriate for this study since it provides a method for selecting pasture areas in close proximity.

The spatial locations of poultry houses were determined using a GIS layer produced by the Arkansas State Highway Transportation Department (AHTD). This layer reports 2,549 poultry houses within the IRDAA watershed boundary, with 1,487 and 1,062 within Washington and Benton counties, respectively. However, on an average, only 71% and 43% of these poultry houses were considered active in Benton and Washington counties, respectively (Storm et al., 2006). It should also be noted that some export of poultry litter from the IRDAA occurs, but no reliable estimates for the entire modeling duration were available.

Using GIS, circular buffers were created around the poultry houses to denote the maximum distance for poultry manure land application. All the pastures within the buffer's radius were assumed to have received poultry manure application. It was also assumed that cows only grazed the pastures that received poultry litter. Based on the methodology used by Lin et al. (2009), it was found that a 0.94 km radius buffer gave the best agreement between the estimated numbers of cows and the pasture area. Since HRUs do not have spatial definition within the model, poultry litter was simulated on pasture HRUs with areas equal to the area of the pastures within the 0.94 km radius buffer. The application rate in these pasture areas was set at 4.5 Mg ha^{-1} $year^{-1}$ for Fescue and 6.7 Mg ha^{-1} $year^{-1}$ for Bermuda grasses for periods between 1995 and 2003, and 2.6 Mg ha^{-1} $year^{-1}$ for both grass types from 2004 onward based on a study conducted by Sharpley et al. (2009). Similar to point-source input, the SWAT model provided the necessary flexibility to incorporate and evaluate such time-variant pasture management practices.

There were 19 ADEQ active permits listed for hog and pig farming in the watershed (ADEQ, 2009). Pig/hog manure production data in these permits included total annual production volume, acreage, and rates of land application. This information was obtained through management plans that were submitted as part of the permit. In addition, the permit reports the geographic location of the production farm. Due to high ratio of water to nutrients in pig/hog manure, it is not economically profitable to transport the manure over long distances. Hence, it was assumed that pig/hog manure was applied in close proximity to the production facility. This was ascertained using one permit in the watershed, which reported the geographical coordinates of the land application sites near the hog farm. Pasture HRUs were selected for land application of swine manure with areas approximately equal to those reported in permits.

Urban lawn management operations were represented through fertilization, lawn mowing, and irrigation. Lawn mowing was implemented on urban HRUs through the removal of biomass. The suggested height for lawn mowing is no more than one-third (or 33%) of the leaf blade (Patton and Boyd, 2007). Further, most homeowners let 100% of the clippings fall on the ground as residue (A. Patton, personal communication, 19 May 2009). Lawn mowing was scheduled twice a month between April and May, once every week in June to September, and once in October (Patton and Boyd, 2007). Nitrogen recommendations for Bermuda grass in lawns are 36.61 kg ha^{-1} in May and September and 48.82 kg ha^{-1} in June and July (Patton, 2007). However, based on data from all 50 U.S. states, Augustin (2007) reported that homeowners typically apply 50% to 70% below published best management practices. To account for this only 40% of the above nitrogen recommendations were included in the SWAT model. Hence, nitrogen applications of 14.6 kg ha^{-1} in May and September and 19.5 kg ha^{-1} in June and July were simulated. TP recommendations are based on soil tests in the watershed; hence, this operation was represented in the SWAT model through auto-fertilization (table 3.3). Assuming that only 50% of the homeowners applied irrigation on their lawns (A. Patton, personal communication, 19 May 2009), 50% of urban HRUs were set for auto-irrigation.

3.3.4 Model Sensitivity Analysis, Calibration, and Validation

Because of the large number of calibration parameters in the SWAT model, it was critical to identify those that greatly affect the output of interest. A combination of Latin hypercube (LH) and one-factor-at-a-time (OAT) sampling, embedded in the SWAT 2009 model, was used for conducting the sensitivity analysis. The combination method allowed consideration of a full range of input

Table 3.3: Management operations for lawns in residential areas.

Operation	Data and Timing
Fertilization	May and September: 14.64 kg ha^{-1} N, auto-fertilize P; June and July: 19.53 kg ha^{-1} N, auto-fertilize P.
Irrigation	Auto-irrigation, 50% of urban HRUs.
Mowing	Frequency: bi-monthly in April and May; weekly in June, July, August, and September; and once in October. Amount: 33% of grass height mowed and 100% returned to ground as residue.

variables and could be implemented with minimal computational cost (van Griensven et al., 2006). Following completion of the sensitivity analysis, SWAT 2009 ranked all user-defined parameters in ascending order of their impact on model output in the sensresult.out output file. While the modeler may use any of these parameters for calibration, it is important to target those parameters that best describe the process with which simulation error is associated (White and Chaubey, 2005).

The locations of seven spatially distributed monitoring stations in the IRDAA for model calibration along with unique subwatersheds that drain into each gauge are shown in figure 3.2. Continuous monitoring in the watershed is conducted primarily by two agencies: USGS and Arkansas Water Resources Center (AWRC). Streamflow data from all USGS stations and water quality data collected by AWRC at the Illinois River near Siloam Springs, Ballard Creek, and Moore's Creek were used. The water quality data collected by AWRC were at a higher frequency compared to other USGS gauges in the watershed and specifically targeted stormflow events. Such high-frequency water quality sampling reduces errors in measured data (Green and Haggard, 2001) and hence was chosen to calibrate the model.

A spatially robust multi-site model calibration results from selection of gauges that drain distinct land uses, soils, slopes, and/or management practices (Migliaccio and Chaubey, 2007).

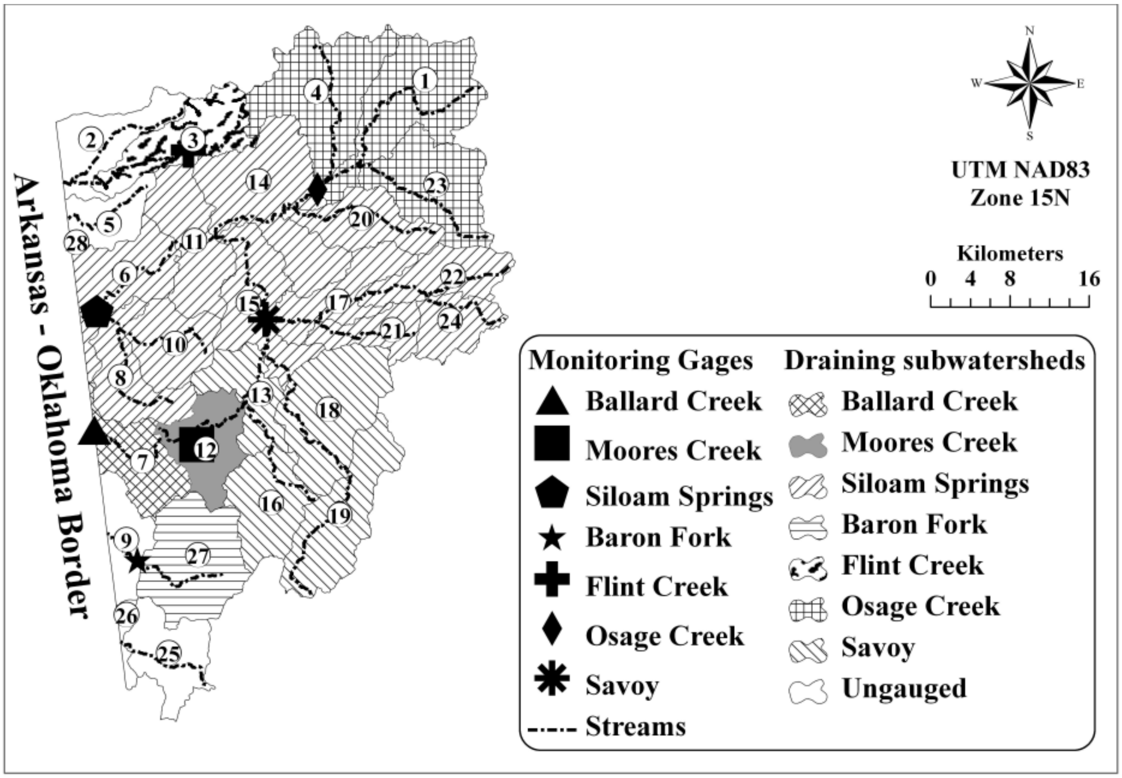

Figure 3.2: Location of monitoring gauges used for the IRDAA SWAT model calibration and/or validation. Each subwatershed has been numbered to facilitate discussion in the text.

USGS gauges on the Illinois River near Siloam Springs and Savoy provide such a scenario (fig. 3.2). While an option existed to choose either one of them based on this rationale, only the Siloam Springs gauge was selected for both calibration and validation because it represents a larger drainage area, whereas the gauge at Savoy was used only for model validation. In contrast, the gauge at Osage Creek provides a drainage area with a unique management scenario. The gauge at Siloam Springs is dependent on the gauge at Osage Creek (fig. 3.2). Based on the selection criteria for calibration and validation gauges argued earlier, calibration at Osage Creek would seem to be a redundant effort if Siloam Springs is already included for calibration purposes. However, the Osage Creek gauge was still included for flow calibration and validation because: (1) it is substantially affected by point sources (Ekka et al., 2006), and (2) it is included in the Arkansas list of 303(d) impaired waterbodies. Due to the marked impairment of this waterbody, inclusion of this gauge could not only better capture the watersheds spatial variability but also increase confidence in the model results.

Model calibrations were first performed at an annual time scale to reduce gross errors, followed by a monthly time scale to account for seasonal trends. The calibration parameters for various model outputs were constrained within the ranges shown in table 3.4. Model outputs for annual calibration were guided by a single objective criterion for relative error (RE) (flow <15%, sediment <20%, and nutrients <25%) (Santhi et al., 2001). Monthly calibration was carried out by calculating the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE; Nash and Sutcliffe, 1970), ratio of RMSE to the standard deviation of measured data (RSR; Moriasi et al., 2007), and percent bias (PBIAS; Moriasi et al., 2007). Because the ultimate use of this model is to identify priority watersheds based on average annual concentration trends, emphasis was placed on PBIAS statistics to quantify the model's bias toward estimating annual average flow, sediment, TP, and NO_3-N. The thresholds and their evaluation criteria (very good, good, satisfactory, and unsatisfactory) provided by Moriasi et al. (2007) were used for each statistic .

Table 3.4: Description of SWAT variables used for the model calibration.

Variable	Process	Scale	Description	Model Range
ALPHA_BF	Base flow	Subwatershed	Base flow alpha factor	0 to 1
SOL_AWC	Base flow	Subwatershed	Soil available water capacity	0 to 1
CN2 (URHD)	Surface flow	Subwatershed	SCS curve number	0 to 100
ESCO	Surface flow	Watershed	Soil evaporation compensation factor	0 to 1
GWQMIN	Base flow	Subwatershed	Threshold depth of water in the shallow aquifer for return flow to occur	0 to 1000
PRF	Sediment	Watershed	Peak rate factor for sediment routing in subbasin	0 to 2
SPEXP	Sediment	Watershed	Exponential factor for sediment routing in main channel.	1 to 1.5
SHALLST_N	Nitrate	Subwatershed	Nitrate concentration in shallow aquifer	0 to 1000
SDNCO	Nitrate	Watershed	Denitrification threshold water content	0 to 1
CDN	Nitrate	Watershed	Denitrification exponential rate coefficient	0 to 3
PPERCO	TP	Watershed	Phosphorus percolation coefficient	10 to 17.5
PHOSKD	TP	Watershed	Phosphorus partitioning coefficient	100 to 200
NPERCO	Nitrate	Watershed	Nitrogen percolation coefficient	0.1 to 1

3.3.5 Prioritization

At the subwatershed scale, SWAT outputs are available in two files, (1) the loadings from uplands (HRUs) in output.sub, and (2) the sum of overland, in-stream, and point sources in output.rch. In watersheds with point-source loadings, the ideal dataset for subwatershed prioritization would be the one that accounts for overland contribution, point sources, and in-stream processes. Although output.rch contains this information, it cannot be used directly for watershed prioritization because the loads are impacted by upstream watersheds. In other words, the use of output.rch directly for determining prioritization can result in downstream subwatersheds unnecessarily getting higher priority due to accumulation of loading from upstream subwatersheds, not because of their higher individual contribution to the entire watershed pollutant load. Hence, a different approach was developed, as discussed below, to calculate individual subwatershed contributions considering pollutant loads from all sources.

In this approach, monthly sediment, TP, and NO_3-N loadings were obtained from point and nonpoint sources by using the output.rch file. Individual subwatershed contributions were determined on a monthly basis by subtracting the loads from upstream subwatersheds. Preliminary analysis revealed that certain subwatersheds acted intermittently as sources and sinks for sediment and nutrients during different times of the year. Previous field studies in this region also demonstrated such source and sink effects in streams (Haggard et al., 2001; Haggard et al., 2003). The source and sink effect added complexities while determining the contributions from individual subwatersheds. For example, if subwatershed A, acting as a source during a particular month, drains into subwatershed B, which acts as a sink during that month, then the contribution of subwatershed B during that month (i.e., load B minus load A) would be a negative number. This presented a challenge for determining the annual contribution from individual subwatersheds since negative numbers can result in lower estimated loading. Therefore, when calculating the annual average contributions from subwatersheds, zero values were used for months during which subwatersheds acted as sinks for sediment and nutrients.

Once the subwatershed contributions were obtained, the next question was whether to use pollutant loads or concentrations for prioritization. Preliminary analysis of the annual loads showed considerable inter-year variability during the validation period (2006-2008). Long-term monitoring data at the outlet demonstrate that annual loads in the IRDAA are strongly tied with discharge (fig. 3.3). Similar relationships were also observed at other monitoring locations but are not presented for the sake of brevity. Haggard (2010) observed that it is difficult to see the effects of changing management practices when evaluating only annual loads from the IRDAA watershed. A significantly decreasing trend from 2002 onward was observed by Haggard (2010) when concentration data were used. Other researchers also agree that concentrations are more suitable than loadings for catchment water-quality studies and reflect the health of the watershed (Johnson et al., 1997; Ahearn et al., 2005). Consequently, annual loadings were divided by annual flow to calculate average annual concentrations for the validation period (2006-2008). The flow-weighted concentration approach for subwatershed prioritization was adopted to normalize the pollutant loading from inter-year rainfall and streamflow variability.

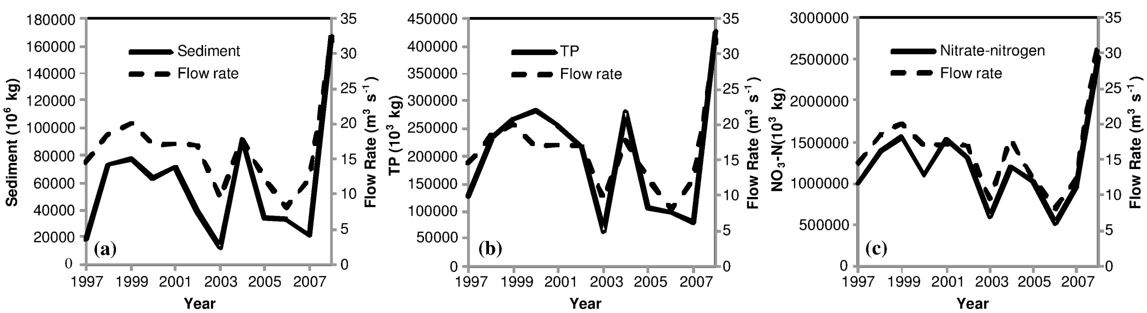

Figure 3.3: Relationship between discharge and pollutant load on the outlet of the IRDAA watershed: (a) sediment, (b) total phosphorus (TP), and (c) nitrate-nitrogen (NO_3-N).

The range of flow-weighted concentration data distribution was divided into five categories using the percentile classification method. Percentile ranking helps in assessing the relative contribution of a subwatershed to the pollutant load, which is useful from a targeting perspective (Robertson et al., 2009). Following prioritization, linkages between various subwatershed metrics and their priority were established to validate the priority results.

3.4 Results and Discussion

3.4.1 Model Calibration and Validations

A total of 41 different input parameters, requiring 410 model simulations, relating to flow, sediments, TP, and NO_3-N yield were selected for sensitivity analysis. This time-consuming process was expedited by compiling the SWAT source code on the high-performance computer at the University of Arkansas and using its dedicated compute nodes to schedule sensitivity analysis simulations. The parameters selected for sensitivity analysis were based on a review of the calibration parameters used in past studies (Santhi et al., 2001; White and Chaubey, 2005; Van Liew et al., 2007). One of the outputs of sensitivity analysis is parameter ranking based on the relative magnitude of the effect that the parameters had on the selected output variable. The top five ranking parameters for various outputs are listed in table 3.5. These parameters were used as starting points for model calibration; however, depending on the error type and underlying process causing the error, other parameters were also selected (table 3.4).

Table 3.5: List of top five parameters and their ranking identified during sensitivity analysis for each model output.

	Ranking				
Output	1	2	3	4	5
Total flow	ALPHA_BF	SURLAG	RCHRG_DP	ESCO	CN2
Sediment	SPCON	ALPHA BF	PRF	SPEXP	SURLAG
Organic P	CN2	SURLAG	BLAI	SOL_ZWC	CH_K2
Mineral P	SOL_Z	SOL_AWC	ALPHA_BF	CN2	ESCO
NO_3-N	RCHRG_DP	CN2	CH_K2	BLAI	ALPHA_BF

The goal of annual calibration was to minimize RE at the annual time scale. While the model always simulates on a daily scale, to support calibration the modeler can print the output at a daily, monthly, or annual scale by adjusting the IPRINT variable in the file.cio input file. Model calibrations were started at the upstream gauge (Osage Creek) and continued to the downstream gauge (Siloam Springs) to logically reduce the spatial accumulation of error. Other calibration sites at headwater subwatersheds (Flint Creek, Ballard Creek, and Baron Fork) were calibrated simultaneously. Calibration of the output also followed a logical order, with streamflow calibrations first, then surface and base flows, followed by sediment, TP, and NO_3-N. This order reduces the process-based propagation of error and corresponds to the typical ascending order of sampling errors of these constituents (White and Chaubey, 2005).

Maximum effort was spent on reducing the hydrological errors, since hydrology is the driving force for all subsequent watershed processes. Once total flow was within 15% of the observed annual average, the model parameters were adjusted to reproduce proper runoff and base flow volumes. For the measured data, we used the base flow filter developed by Arnold and Allen (1999) to calculate the relative contributions of surface flow and base flow. Thereafter, the SWAT model was calibrated for annual sediment load.

Two dominant processes that control sedimentation in watersheds are upland erosion and transport, and fluvial transport. The parameters related to these processes were adjusted for capturing sedimentation in the IRDAA. Once sediment loading was calibrated, the TP loadings were mostly in the range of observed values and required only minor adjustment in the model parameters, such as PPERCO and PHOSKD. NO_3-N loading was calibrated by adjusting the parameters affecting the denitrification process in the model, such SDNCO and CDN. Results of annual calibrations at various gauges are presented in tables 3.6 and 3.7. The model was able to successfully capture the hydrology ($<$15% RE), sediment ($<$20%), and nutrients ($<$25%) within the thresholds recommended by Santhi et al. (2001).

Once annual calibrations were satisfactory, monthly calibration was conducted. In contrast to annual calibration, which had just one model performance evaluation criterion (RE), four statistical criteria (R^2, NSE, RSR, and PBIAS) and time-series graphs of measured and simulated data were used for evaluation of monthly calibration results. However, only statistical results are presented in this article for brevity (tables 3.8 and 3.9). For monthly total flow predictions during the calibration period, R^2 ranged from 0.42 (Ballard Creek) to 0.85 (Baron Fork), NSE ranged from 0.51 (Flint Creek) to 0.78 (Ballard Creek), PBIAS ranged from 2.11% (Ballard Creek) to 7.85% (Baron Fork), and RSR ranged from 0.53 (Baron Fork) to 0.72 (Flint Creek). Based on the performance evaluation guidelines suggested by Moriasi et al. (2007), the simulated total flow values at all the

Table 3.6: Annual streamflow calibration (1996-2005) results.

Gauge	Output	Average (m^3 s^{-1}) Measured	Average (m^3 s^{-1}) Simulated	Standard Deviation (m^3 s^{-1}) Measured	Standard Deviation (m^3 s^{-1}) Simulated	R^2	RE[a] (%)
Flint Creek	Total flow	0.9	0.9	0.2	0.2	0.7	1.4
	Surface flow	0.4	0.4	0.2	0.2	0.5	11.4
	Base flow	0.4	0.4	0.1	0.1	0.5	-2.9
Siloam Springs	Total flow	15.2	15.4	3.4	3.7	0.7	-1.0
	Surface flow	7.3	7.4	2.4	3.1	0.8	-0.7
	Base flow	7.9	7.9	1.4	2.6	0.6	0.8
Baron Fork	Total flow	1.2	1.2	0.4	0.4	0.8	1.2
	Surface flow	0.8	0.8	0.4	0.4	0.9	4.7
	Base flow	0.3	0.3	0.1	0.1	0.7	-0.9
Ballard Creek[b]	Total flow	1.0	1.1	0.1	0.1	0.6	-1.7
	Surface flow	0.2	0.2	0.1	0.1	0.9	5.9
	Base flow	0.8	0.8	0.1	0.1	0.9	2.6
Osage Creek	Total flow	4.2	4.7	0.8	0.8	0.5	3.7
	Surface flow	1.6	1.8	0.4	0.4	0.7	1.3
	Base flow	2.6	2.9	0.5	0.4	0.4	7.9

[a] RE = relative error.
[b] Ballard Creek subwatershed was calibrated for 2003-2005 based on data availability.

five gauges during the calibration period can be described as “satisfactory” to “very good” with the exception of the RSR value at Flint Creek. These results are comparable or better than those obtained in previous multi-site SWAT calibration studies by White and Chaubey (2005) and Qi and Grunwald (2005). The statistics for the relationship between measured and simulated data during the validation period for different criteria were R^2 = 0.71 to 0.85, NSE = 0.50 to 0.85, PBIAS = -11.40 to 22.7, and RSR = 0.12 to 0.70.

It is clear from the statistics at Ballard Creek that the model simulations failed to capture base flow at this gauge. Ballard creek is unique hydrologically because of different patterns of ground-water inflow relative to the other sites. Base flow contributions within the subwatershed for the years 2003, 2004, and 2005 were 89%, 78%, and 75%, respectively. In contrast, the average base flow contribution at the outlet of the watershed (Siloam Springs) was 52%. About 83% of the soil within the Ballard Creek (subwatershed 7) belongs to hydrologic group C, indicating that the higher base flow observed could not be attributed to soil infiltration characteristics. Interestingly, a karst area sensitivity map of Washington County, developed by The Nature Conservancy, rated

Table 3.7: Annual sediment and nutrient calibration (1996-2005) results.

		Average		Standard Deviation			RE[a]
Gauge	Output	Measured	Simulated	Measured	Simulated	R^2	(%)
Siloam Springs	Sediment (t ha^{-1})	0.32	0.32	0.17	0.13	0.8	-1.5
	TP (kg ha^{-1})	1.22	1.03	0.49	0.39	0.8	15.6
	Nitrate (kg ha^{-1})	7.17	6.61	1.79	2.88	0.5	7.9
Ballard Creek[b]	Sediment (t ha^{-1})	0.26	0.26	0.10	0.08	0.6	-2.2
	TP (kg ha^{-1})	1.63	2.01	0.40	0.52	0.8	-23.7
	Nitrate (kg ha^{-1})	12.00	12.91	3.37	1.32	0.9	-7.5

[a] RE = relative error.
[b] Ballard Creek subwatershed was calibrated for 2003-2005 based on data availability.

the groundwater connectivity in Ballard Creek as "high" to "extremely high" (NWARPC, 2007). Although karst-based hydrological calibrations in SWAT have been demonstrated by Baffaut and Benson (2009), an explicit spatial dataset reported in their study is unavailable for the IRDAA watershed. Nonetheless, this shows the extent of variation in hydrology within a watershed and highlights the value of a multi-site calibrated model in understanding and capturing diverse hydrological trends.

Sediment calibration and validation was conducted at the Siloam Springs and Ballard Creek stations, whereas the Moore's Creek gauge station was used for validation only. The sediment output from the Sed_Out variable was used to calculate the sediment loading rate on a per hectare basis (i.e., tons ha^{-1}). The monthly calibration and validation statistics for sediment are shown in table 3.9. While all statistics are within the satisfactory range, PBIAS showed that the model consistently underpredicted the sediment output. This resulted primarily when the model was unable to capture sediment peaks during storm events. SWAT's inability to capture sediment load during peak events has been attributed to its inability to account for floodplain erosion during high flow events (Benaman and Shoemaker, 2005).

The TP simulations from SWAT were calculated as a sum of organic P (ORGP_OUT) and mineral P (MINP_OUT) (White and Chaubey, 2005). Following hydrological and sediment calibrations, the model closely followed the temporal pattern of the monthly measured data, as confirmed by the R^2 values of 0.82 and 0.84 for the calibration period at Siloam Springs and Ballard Creek, respectively. This was not surprising because transport of TP loads in the IRDAA is strongly

Table 3.8: **Monthly streamflow calibrations and validation results.**

Gauge	Output	Calibration Statistics (1996-2005)				Validation Statistics (2006-2008)			
		R^2	NSE	PBIAS	RSR	R^2	NSE	PBIAS	RSR
Flint Creek	Total flow	0.73	0.51	3.96	0.72	Calibration only			
	Base flow	0.45	-1.46	6.40	1.56				
	Surface flow	0.76	0.55	1.71	0.67				
Siloam Springs	Total flow	0.73	0.53	2.71	0.68	0.76	0.56	8.99	0.12
	Base flow	0.65	0.25	-3.42	0.86	0.68	0.46	7.67	0.87
	Surface flow	0.67	0.37	9.25	0.79	0.69	0.47	3.49	0.78
Baron Fork	Total flow	0.85	0.71	7.85	0.53	0.71	0.50	6.98	0.70
	Base flow	0.76	0.55	-16.42	0.67	0.31	0.38	19.17	0.95
	Surface flow	0.85	0.71	17.06	0.53	0.74	0.69	-0.19	0.68
Ballard Creek[a]	Total flow	0.42	0.78	2.11	0.63	0.81	0.66	-11.40	0.68
	Base flow	-0.31	-0.38	3.14	4.11	0.44	-0.41	-38.39	7.0
	Surface flow	0.51	0.88	-2.12	0.5	0.80	0.63	26.11	0.62
Osage Creek	Total flow	0.78	0.57	3.86	0.65	0.85	0.63	22.7	0.60
	Base flow	0.70	0.09	5.04	0.95	0.73	0.30	37.9	0.83
	Surface flow	0.78	0.57	2.27	0.65	0.82	0.57	7.82	0.65
Savoy	Total flow	Validation only				0.71	0.85	1.92	0.53
	Base flow					0.19	0.51	-14.31	0.89
	Surface flow					0.75	0.87	7.87	0.49
Moore's Creek	Total flow	Validation only				0.75	0.56	-1.72	0.65
	Base flow					0.31	0.07	8.91	0.94
	Surface flow					0.80	0.61	0.21	0.61

[a] Ballard Creek was calibrated for 2003-2005 based on data availability.

dependent on precipitation and runoff in the watershed (Haggard, 2010). During the validation period, the R^2 values were 0.82, 0.82, and 0.84 at Ballard Creek, Siloam Springs, and Moore's Creek, respectively. The NSE ranged from 0.59 to 0.74 during calibration and validation, respectively. This puts the model results in the "satisfactory" and "good" category for the calibration and validation periods.

The NO_3-N simulations were extracted from the SWAT reach output file using the NO3_OUT variable. The R^2 values for NO_3-N simulation at Siloam Springs were 0.56 and 0.66 during the calibration and validation periods, respectively. However, the model was unable to capture the pattern at Ballard Creek, which can be seen from the unsatisfactory R^2 and NSE values. This could be because the model was unable to capture the base flow pattern for this subwatershed, as seen in the results earlier. Green and Haggard (2001) also concur about the strong influence of

Table 3.9: Monthly sediment and nutrient calibration and validation results.

Gauge	Output	Calibration Statistics (1996-2005)				Validation Statistics (2006-2008)			
		R^2	NSE	PBIAS	RSR	R^2	NSE	PBIAS	RSR
Moore's Creek	Sediment (t ha^{-1})	Validation only				0.60	0.01	13.2	0.98
	TP (kg ha^{-1})					0.84	0.70	8.1	0.54
	Nitrate (kg ha^{-1})					0.79	0.60	27.0	0.62
Siloam Springs	Sediment (t ha^{-1})	0.79	0.55	12.64	0.67	0.92	0.81	1.0	0.43
	TP (kg ha^{-1})	0.82	0.59	23.42	0.63	0.82	0.74	-7.02	0.57
	Nitrate (kg ha^{-1})	0.56	-0.30	10.67	1.14	0.66	0.21	53.09	0.88
Ballard Creek[a]	Sediment (t ha^{-1})	0.90	0.81	15.8	0.43	0.64	0.36	27.0	0.79
	TP (kg ha^{-1})	0.84	0.70	14.39	0.60	0.82	0.63	-11.89	0.60
	Nitrate (kg ha^{-1})	0.40	-0.48	7.89	1.21	0.38	-0.26	42.70	1.1

[a] Ballard Creek was calibrated for 2003-2005 based on data availability.

groundwater on NO_3-N in the IRDAA watershed.

3.4.2 Subwatershed Prioritization

The results of subwatershed prioritization based on the individual contribution from subwatersheds are shown in figure 3.4. The water quality data output (concentration) for the entire validation period (2006-2008) was used for this purpose. The range of flow-weighted concentration data was divided into five percentile categories: 0-20, 21-40, 41-60, 61-80, and 81-100.

The spatial distribution of priority subwatersheds showed greater sediment contribution from the northern and eastern portions (subwatersheds 1, 2, 4, 5, and 23), TP contribution from northern and eastern portions (subwatersheds 2, 3, 4, 5, and 23), and NO_3-N contribution from the northern and western subwatersheds (subwatersheds 2, 4, 5, 6, and 7). In addition, a lower sediment contribution can be seen from the southern and central subwatersheds (subwatersheds 11, 15, 16, and 25), TP from the central subwatersheds (subwatershed 6, 11, 15, and 16), and NO_3-N contribution from southern and eastern subwatersheds (subwatershed 9, 21, 22, and 27).

Because there are no data to quantitatively validate these results, we examined several subwatershed metrics and known water quality impairments to verify the model-generated priority results. The spatial distribution of land use in 2006 showed that the watershed is largely forested in the southern part with a mix of forest and pasture land cover in other parts. Urbanization in

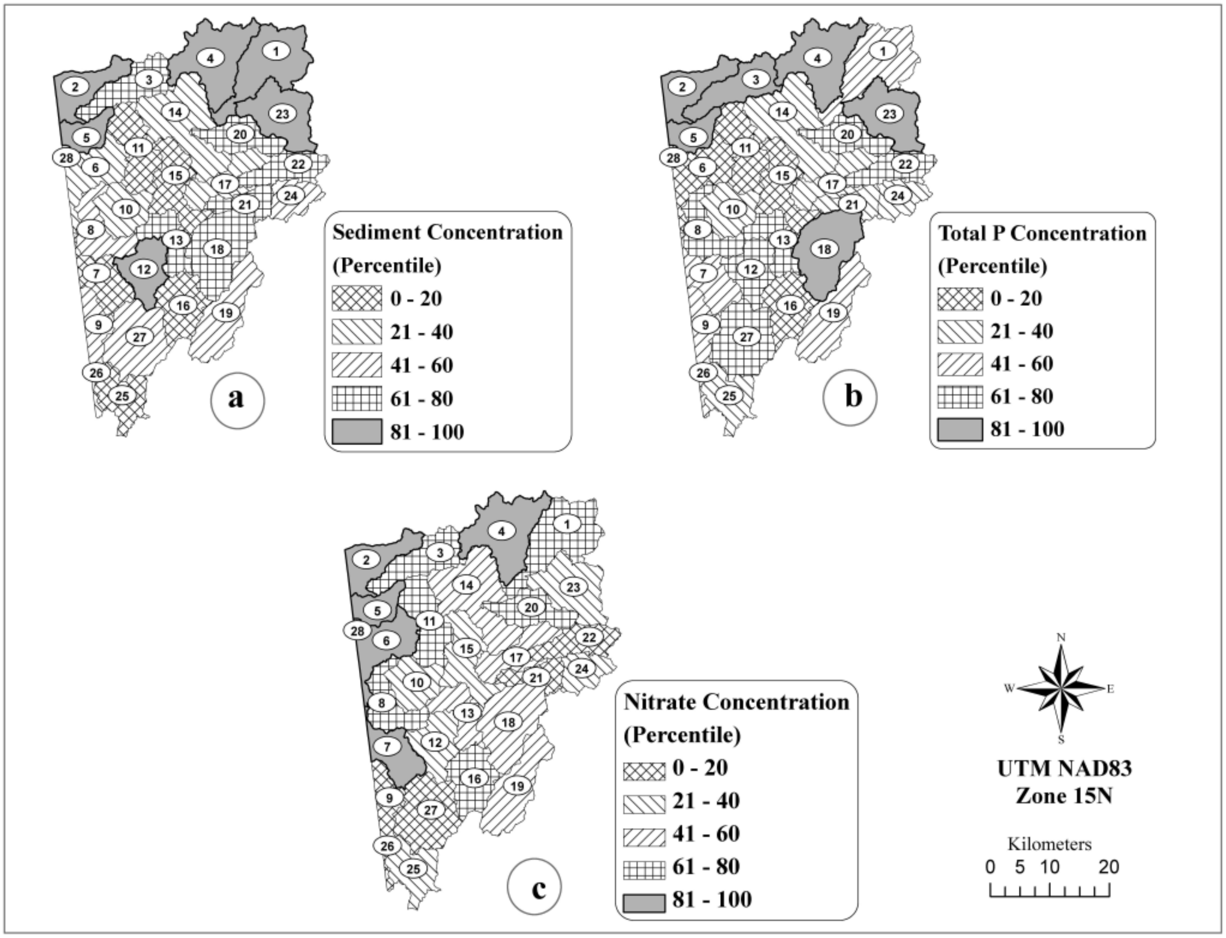

Figure 3.4: Simulated subwatershed pollutant concentration: (a) sediment, (b) total phosphorus, and (c) nitrate-nitrogen.

the IRDAA is a recent phenomenon and is fairly localized in the eastern portion of the watershed. Hence, subwatershed forest and pasture acreage were related with model-derived pollutant concentrations (fig. 3.5). It was observed that, in general, subwatershed pollutant concentrations were negatively correlated with percentage of forest acreage and positively correlated with pasture acreage. This was expected because agriculture is known to be a major source of nonpoint-source pollution (USGS, 1999). Similar relationships were also observed from short-term intensive monitoring studies conducted by Haggard et al. (2003) and Migliaccio et al. (2007). These figures provide a simple and rapid way to validate modeling priorities. One must be warned, however, not to link subwatershed priorities entirely to land uses (i.e., nonpoint sources) only. Presence of point-source discharges in a subwatershed can result in priorities that greatly deviate from this relationship (for example a forest-dominated watershed may appear as top priority). It is important to consider both point and nonpoint sources when evaluating priority subwatersheds.

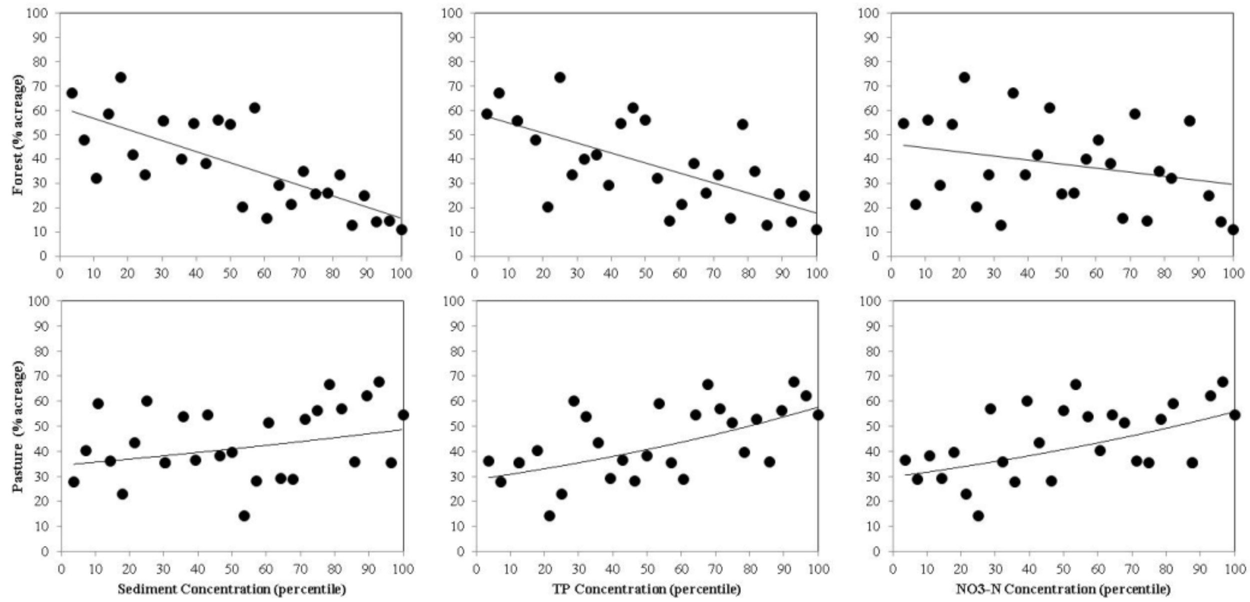

Figure 3.5: Relationship between subwatershed pollutant concentration (percentile) and its forest and pasture acreage (percentage).

The resulting priority subwatersheds comprised only 24% of the total area of the watershed but contributed 49% of sediments, 33% of TP, and 27% of NO_3-N annual average loadings. Similar disproportionate loading from priority subwatersheds has been previously reported (Tripathi et al., 2003). SWAT simulations also showed that higher sediment concentrations resulted from subwatersheds that had dominant urban and pasture land uses and/or a majority of soils in hydrologic group C and D and more acreage with slopes of >3%. Higher runoff and erosion can be expected from group C and D soils. For example, the headwaters of Osage Creek (subwatershed 1), which is categorized in the 80-100 percentile category for sediment priority, was 78% urban and pasture land use and only 15% forest land use per the 2006 LULC map. A majority (>71%) of the area in this subwatershed has soils in hydrologic groups C and D, and about 58% of the area has slopes in the 3% to 8% and >8% categories. A combination of high slopes and soil runoff potential could be the source of large erosion from some landscapes in this subwatershed.

Similarly, subwatersheds with high priority based on TP concentration had an average of 50%

pasture land use and 26% urban land use. In addition, four of the six highest TP priority subwatersheds had waterbodies that were included in the 2008 Arkansas 303(d) list owing to impairments from point sources. The subwatersheds with high priority based on NO_3-N concentration had an average of 56% pasture land use and 12% urban land use. One of the highest NO_3-N priority subwatersheds (subwatershed 5) was also included in the 2008 303(d) list due to impairments from point sources. Spatial comparison of NO_3-N concentration with the SSURGO soil map (not shown here) showed that a higher percentage of hydrologic group B soils (e.g., Clarksville soil series) in the central subwatersheds could partially explain the higher nitrate leaching. Medium to low nitrate contributions from the southern forested subwatersheds are in agreement with results of Popova et al. (2006). The lowest priority subwatersheds based on NO_3-N concentrations were those with an average of 43% forest cover. The effect of soils and slope did not seem to be pronounced in TP and NO_3-N priority subwatersheds.

Regardless of the exact source of pollutant in priority subwatersheds, linkages between subwatershed characteristics and water quality serve to augment the model-generated priority results. These associations have a scientific background as seen from previous work (Haggard et al., 2003; Migliaccio et al., 2007; Ghebremichael et al., 2010). Using this approach, watershed modelers can rapidly validate responses at uncalibrated subwatershed outlets and suggest potential sources that may explain subwatershed priority. These results are specifically aimed to help in planning further in-depth studies in priority subwatersheds to identify the exact cause and accordingly devise a management course of action.

3.5 Summary and Conclusions

Watershed-scale pollutant loading requires the co-existence of sources (upland, in-stream, and point sources) and fluvial transport. While accumulation of pollutants in downstream subwatersheds is a function of fluvial transport, reduction of pollutant loads can be best accomplished by targeting both point and nonpoint sources of pollution. In the IRDAA watershed, pollutant management practices and land uses have changed in the past 10 to 15 years. Distributed subwatershed responses from the SWAT model can be used for prioritizing based on holistic contribution. However, proper model setup, multi-site calibration and validation, and use of relevant output data are critical components of the subwatershed prioritization process. In this article, we have provided a case study that will help other modelers to critically examine the use of distributed results from SWAT for subwatershed prioritization through four objectives.

3.5.1 Objective 1: Model Setup

We used the ArcSWAT interface in combination with the SWAT 2009 algorithm to set up the SWAT model for the IRDAA watershed. The subwatershed boundaries were established using the predefined 12-digit HUC boundary layer. Other spatial datasets included were SSURGO soil, hydrography, elevation, interpolated rain gauge and NEXRAD precipitation, and multi-year land use maps. Other temporal data inputs included effluent discharge from WWTPs and detailed land management data. SWAT provided the necessary framework to input and evaluate time-variant detailed management practices in the IRDAA.

3.5.2 Objective 2: Model Calibration and Validation

A combination of sensitivity analysis and literature review was used to identify key calibration parameters. Calibrated output involved total flow, surface flow, base flow, sediment, total phosphorous, and nitrate-nitrogen. The model was calibrated and validated at seven locations for hydrology and three locations for water quality outputs, first at annual scale and then at monthly scale. A multi-objective function consisting of percent relative error (RE), Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), coefficient of determination (R^2), and ratio of the root mean square error to the standard deviation of measured data (RSR) was used to guide model evaluations. The model outputs were generally found to be satisfactory or better and within ranges reported in previous SWAT publications. Results also showed that multi-site calibration and validation provided a means to gain more confidence in the model's predictive abilities at the outlet and other spatially distributed locations within the watershed. We found that hydrological patterns at the outlet might differ from one or more internal locations. In such conditions, calibrating at the outlet only may limit our understanding of model performance.

3.5.3 Objectives 3 and 4: Subwatershed Prioritization and Validation

The average annual flow-weighted concentrations were used to prioritize 12-digit subwatersheds based on their individual contributions of sediment, TP, and NO_3-N. The priority subwatersheds comprised only 24% of the total area of the IRDAA watershed but contributed 49% of sediments, 33% of TP, and 27% of NO_3-N annual average loads.

Linkages between subwatershed characteristics and water quality were established, which served as surrogates for rapidly validating the priority watersheds. In general, the highest priority subwatersheds based on the constituent of interest were found to be associated with urban and pasture land uses, while slopes and soil hydrologic groups also seemed to play a role. The lowest priority subwatersheds in general were found to be associated with high forest and low urban land use dominated subwatersheds, with no evidence of association with the subwatersheds' slopes and soil hydrologic groups. Known water quality impairments also served to validate the priority watersheds. Selecting these subwatersheds ahead of others for planning and rehabilitation activities can justify the use of limited resources.

Acknowledgements

We would like to thank the Arkansas Natural Resource Commission (ANRC) for funding this project through the U.S. Environmental Protection Agency 319 Grant Program. Valuable input from several University of Arkansas' subject matter specialists and extension agents contributed immensely in fine-tuning the management data input. Sensitivity analysis and calibration were conducted using the supercomputing facilities at the University of Arkansas, which is supported by the National Science Foundation under Grant MRI 0421099 (Red Diamond) and Grant MRI 072265 (Star of Arkansas). Special thanks go to the Environmental Task Force (ETF) of the University of Arkansas for organizing several discussions to critically review our modeling results.

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Chapter 4

Field_SWAT: A Tool for Mapping SWAT Output to Field Boundaries

4.1 Abstract

The Soil and Water Assessment Tool (SWAT) hydrological/water quality model divides a watershed into hydrological response units (HRUs) based on unique land cover, soil type, and slope. HRUs are a set of discontinuous land masses that are spatially located in the watershed but their responses are not tied to any particular field. Field_SWAT, a simple graphical user interface (GUI) driven tool, was developed to map SWAT simulations from an HRU layer to a user-defined field boundaries layer. This stand-alone tool ingests spatial and non-spatial SWAT outputs and helps in visualizing them at field-scale using four different spatial aggregation methods. The tool was applied for mapping SWAT model's annual runoff and sediment outputs from 218 HRUs to 89 individual field boundaries in an agriculturally dominated watershed in Northeast Arkansas. Area-weighted spatial aggregation method resulted in most suitable mapping between HRU and field outputs. This research demonstrates that Field_SWAT could potentially be a useful tool for field-scale targeting of conservation practices and communicating model outputs to watershed managers and interested stakeholders.

Keywords. *SWAT, hydrological response units, HRU, field responses.*

4.2 Introduction

The variable nature of surface runoff in response to management practices and heterogeneous nature of physiographic characteristics such as topography, geology, and soils represent the challenges that hydrological modelers continuously face while modeling a watershed. Efforts to fully account for and represent management practices along with heterogeneous physiographic characteristics have resulted in the transformation of models from those that consider the entire catchment as a lumped unit to the contemporary, distributed models. The public availability of digital data such as, digital elevation models (DEM), soils, land use/land cover (LULC), precipitation along with advances in computing resources have all contributed towards the push for adoption of distributed models (Johnson, 2009). Distributed models divide a watershed into smaller units to represent spatial variability across the whole area. Models such as the erosion impact calculator (EPIC; Williams et al., 1984), precipitation-runoff modeling system (PRMS; Leavesley et al., 1983), hydrological simulation program - FORTRAN (HSPF; Bicknell et al., 1997), soil and water assessment tool (SWAT; Arnold et al., 1998), MIKE-SHE (Bathurst, 1986), and Modelo de Erosão FÌsico e DIStribuido (MEFIDIS; Nunes et al., 2005) can be categorized as semi- or fully-distributed based on the delineation of smallest land unit for calculating model responses. While SWAT uses the term hydrological response units (HRUs) for denoting smallest modeling unit, several other terms have also been used in the literature such as, grouped response units (Kouwen et al., 1993), hydrologically similar units (Karvonen et al., 1999), and representative elementary areas (Wood et al., 1988).

Delineation criteria for HRUs have evolved with watershed models. Topographic-based HRUs were first delineated by Leavesley et al. (1983) for storm hydrograph simulation in the PRMS model. In this approach, a watershed is conceptualized as a series of interconnected rectangular flow-planes and channel segments. Channel segments are delineated based on the flow direction from the digital elevation model and flow is routed over the flow planes and channel segments. Flugel (1995) introduced the concept of homogeneity of HRUs by lumping land areas having similar physiographic characteristics represented by LULC, soils, and topography. An underlying justification for such delineation is that the dynamics of hydrological processes within an HRU have small variation compared to that among different HRUs. Bongartz (2003) compared the topographical approach by Leavesley et al. (1983) and homogeneous HRU based approach by Flugel (1997) and reported that for smaller catchments ($<$200 km^2) homogeneous HRU provided better representation of the catchment. The SWAT model has adapted the homogenous HRU concept and requires users to specify threshold of land cover, soil, and slope, which is then used to create HRUs (Neitsch et al., 2005). Different thresholds produce different distributions of HRUs. Details of this delineation process have been provided later in this paper. Gitau (2003) suggested that using thresholds resulted in loss of information and should be used only when the number of HRUs created (a function of drainage area and thresholds) results in acceptable computation costs. Gassman (2008) observed that the incorporation of HRUs in SWAT is being regarded as both strength and weakness of the model. Although, the method of HRU delineation has allowed the flexibility to adapt the model to sizes ranging from field plots to entire river basin, the non-spatial nature of HRUs is regarded as a key weakness of the model (Gassman et al., 2007).

Recently, there have been several applications of the SWAT model for identifying priority pollutant-contributing areas at the subwatershed- (Tripathi et al., 2003; Saraswat et al., 2010) and HRU- (White et al., 2009; Ghebremichael et al., 2010) scale. These applications recognize the disproportional nature of pollutant contribution in a watershed and seek to spatially identify those areas that are considered hotspots of pollution. The ultimate aim is to target conservation practices, instead of random implementation, in order to gain maximum pollutant reduction (Parajuli et al., 2008). However, in reality, agricultural conservation practices are applied at the field-scale (whole or part of a field) and hence, field-level targeting is a key to watershed pollution management (Daggupati et al., 2011). Current SWAT HRU outputs do not provide the right spatial-scale for transferring model results to actionable items for watershed pollution management.

Our overall goal in this study was to simplify SWAT model HRU outputs and provide a tool that allows watershed managers and conservation agencies to visualize results to user-defined boundaries, such as fields, so that they can target implementation of conservation practices. To realize this goal, our specific objectives were to (1) develop a spatial algorithm to aggregate HRU level outputs by mapping it to field boundaries within a watershed, and (2) incorporate the algorithm in a user-friendly and stand-alone geospatial software that allows visualization of SWAT HRU output to user-defined field boundaries.

4.3 Methodology

4.3.1 SWAT HRU Delineation Concept

In SWAT models graphical user interface, ArcSWAT, creation of HRU is a two-step process. In the first step, the SWAT model divides the drainage area of the watershed into smaller subwatersheds. These subwatersheds are either delineated based on a user-defined threshold area approach or by using a user-defined subwatershed boundary layer. In the second step, the subwatersheds are further divided into discontinuous land masses, which are delineated, based on (a) aggregation using a user-defined threshold for land cover, soil type, and slope range within each subwatershed, followed by (b) a geographical information system (GIS) based spatial overlay scheme. This process of HRU creation, mentioned in the second step above, can be explained further using an example as illustrated in figure 4.1.

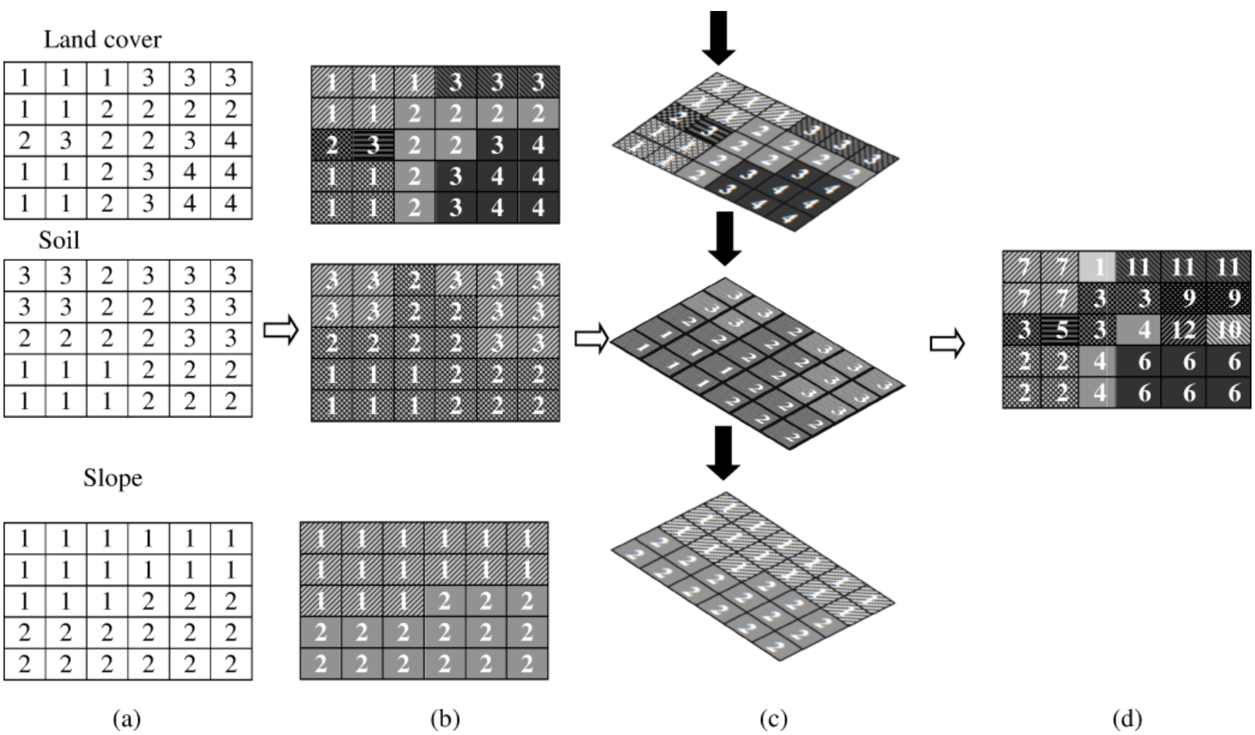

Figure 4.1: Illustration of SWAT model HRU development algorithm. (a) Thematic maps of landcover, soil, and slope; (b) lumped categories within each map after applying a threshold of 20, 30, and 20% for landcover, soil, and slope, respectively. Note: lumped areas have similar cell background; (c) overlay of layers from (b); and (d) final HRU distribution.

In this example, we assume a rectangular subwatershed of size 30 cells (5 × 6) with four, three, and two different types of land cover, soil, and slope categories, respectively (fig. 4.1a). It is further assumed that HRUs have been delineated using a threshold of 20% (6 cells), 30% (9 cells), 20% (6 cells) for land cover, soil, and slope, respectively. This implies that any land cover, soil, and slope occupying less than or equal to six, nine, and six cells, respectively, in the subwatershed will be lumped with the adjacent dominant cells. Because of application of this thresholding for the HRU delineation, category four in land cover and category one in soil will be lumped with adjacent areas since they fall below the threshold (fig. 4.1b). A spatial overlay is performed (fig. 1c) such that all cells having the same combination of land cover, soil, and slope are given a unique HRU identification number (fig. 4.1d and table 4.1). Note that these thresholds were selected only to demonstrate the concept of HRU delineation in the SWAT model and should not be construed as a guideline for other studies.

Table 4.1: Unique combination of landcover, soil, and slope of the HRUs delineated in fig. 4.1.

	HRU ID											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Land cover	1	1	2	2	3	3	1	1	2	2	3	3
Soil	2	2	2	2	2	2	3	3	3	3	3	3
Slope	1	2	1	2	1	2	1	2	1	2	1	2

Several observations can be made from this example. First, there is an evident loss of information since land cover category four and soil-type category one do not exist for model calculations. It may be argued that, in trying to achieve a balance between watershed representation and computational efficiency, some compromises need to be made. However, depending on project goals, one must be aware of which land cover, soil, or slope categories are lost in the process of HRU delineation and decisions be made accordingly. Second, it must be highlighted that not all HRUs are contiguous in nature (for e.g. HRU number 3 in fig. 4.1d). Although, it may appear that only one cell (category 5) separated three other cells belonging to category 3, this pattern of non-contiguity can be more pronounced on a subwatershed scale. The mapping algorithm development, described in the following section, suitably accounts for this fragmented nature of HRU outputs.

4.3.2 Mapping Algorithm

The mathematical foundation for HRU to field level visualization is important to understand at this time. Let the instantaneous state of a typical SWAT model response for a particular subwatershed be described by a vector $X(t) = (x_1, x_2, \ldots, x_i)$. For instance, the vector X may represent runoff or sediment yield from HRU location x_i and at time step t. The responses summed over a period of time can be described as follows:

$$\int_{i=1}^{m} x_i \, dt = v \tag{4.1}$$

where, v is the daily, monthly, or annual SWAT output from a subwatershed with m HRUs.

Now consider a case where we wanted to visualize SWAT output from individual fields for the same subwatershed. In this case, let the instantaneous state of a typical SWAT model response for a particular subwatershed be described by a vector $Y(t) = (y_1, y_2, \ldots, y_j)$. Again, the vector Y may represent runoff or sediment yield from field locations y_j for the same time step t such that,

$$\int_{j=1}^{n} y_j \, dt = w \tag{4.2}$$

where, w is the daily, monthly, or annual SWAT output from a subwatershed with n fields subject to the constraint that

$$v = w \tag{4.3}$$

The main purpose of the algorithm is to calculate y_j (i.e. output from field boundaries) using x_i (i.e. HRU output). This requires an approach for consolidating runoff or sediment loading responses from different HRUs that are encompassed within individual field boundaries. To explain this further, let us consider a typical field scenario with same land cover and soil type but with two different slope classes. As we have seen in the HRU delineation concept earlier, HRUs are land areas with unique land cover, soil, and slope, thus for this field scenario, it would mean the presence of two HRUs, designated as HRU-1 and HRU-2, within this field boundary. It becomes relevant to revisit SWAT models approach for estimating surface runoff and sediment loading. The model estimates surface runoff using the SCS curve number equation (USDA SCS, 1972). Since every part of an HRU receives the same amount of rainfall and has the same soil physical properties, the water depth resulting from precipitation excess is spatially constant within an HRU (Flugel, 1997). Similarly, the SWAT model uses the Modified Universal Soil Loss Equation (MUSLE; Williams, 1975) to calculate sediment yield. All factors governing MUSLE equation are constant within an HRU. Note that there is no routing simulated between HRUs; daily output from all HRUs within a subwatershed are aggregated to calculate the total overland loading. These concepts indicate that field level response could be estimated using some spatial data aggregation method from all the HRUs that are part of a field.

Spatial data aggregation is often preferred in environmental analyses because certain patterns are better revealed at specific scales (Bian and Butler, 1999). Methods of aggregation vary depending upon the type and spatial scale of data. Some of the typical aggregation methods include mean, mode, geometric mean, and area-weighted average (Srinivasan and Arnold, 1994). A computer-based tool developed to implement the mapping algorithm has been discussed in the next section and provides users with the option of aggregating HRU output using any of these four methods.

4.3.3 Field_SWAT for Implementing Mapping Algorithm

The mapping concept was implemented as a user-friendly graphical user interface called Field_SWAT. Field_SWAT is developed using the MATLAB programming environment (MATLAB, 2010) and deployed as a stand-alone (does not require any proprietary software) tool to reach a wide community of users. The tool has been developed to interact specifically with SWAT model developed using ArcSWAT interface and the folder structure that it creates. Field_SWAT has three major components (or panels): Input Data, Display, and Status/Output (fig. 4.2). The input data panel contains three user-driven and sequentially accessible set of tools, which can be used to feed the input interactively for visualizing outputs at field level. The input data panel requires the user to define the base folder (or the Field_SWAT folder) on the computer where subsequently all the data will be stored. Once this folder is identified, three sub-folders are automatically created: Shape, Raster, and Output. These folder names are intuitive and indicate the type of data (vector or raster) that is stored in the respective folders. The functioning of Field_SWAT following this step is explained below and illustrated in figure 4.3.

Once the Field_SWAT folder is created, the user is required to identify the SWAT project folder by using the browse button on the interface. The completion of this step results in the execution of two background tasks by Field_SWAT. During the first task, the Watershed\Grid folder within SWATs project folder is identified and a copy of the HRU layer (hru1.aux) is copied from the Grid folder into the Raster folder of Field_SWAT. It is pertinent to note that HRU boundaries created by ArcSWAT are stored in both vector and raster format. However, we have used HRU raster format layer because the tool is built to process raster data. The HRU layer is a raster, geo-referenced and categorical data layer that contains HRU ID for each cell in the watershed. The HRU layer is created using ESRI (2010) proprietary grid format. Since, one of the objectives of this study was to develop the tool in a stand-alone format (i.e. independent of other software) it was necessary to first convert the grid file to a generic raster storage format. To accomplish this, we incorporated the open-source geospatial data abstraction library (GDAL, 2010) within Field_SWAT, which allows it to instantaneously convert the proprietary grid file to a geo-referenced tag image file format (GeoTiff). This GeoTiff file, a copy of the HRU layer (hru1.aux), is stored in the Raster folder under the name hru1.tif. The GeoTiff format was selected because it is readable by a wide variety of commercial and open-source remote sensing and GIS software. Thereafter, metadata information of the HRU layer (corner coordinates and cell size) is read for creating a three dimensional orthogonal grid (hereafter referred as Field_SWAT grid) that encompasses the total watershed drainage area (fig. 4.4). The number of rows, columns, and cell size is displayed in the status window, which should be helpful to the user in deciding appropriate field size for using the tool. Field_SWAT grid has a three dimensional structure with the x- and y axes representing the latitude and longitude

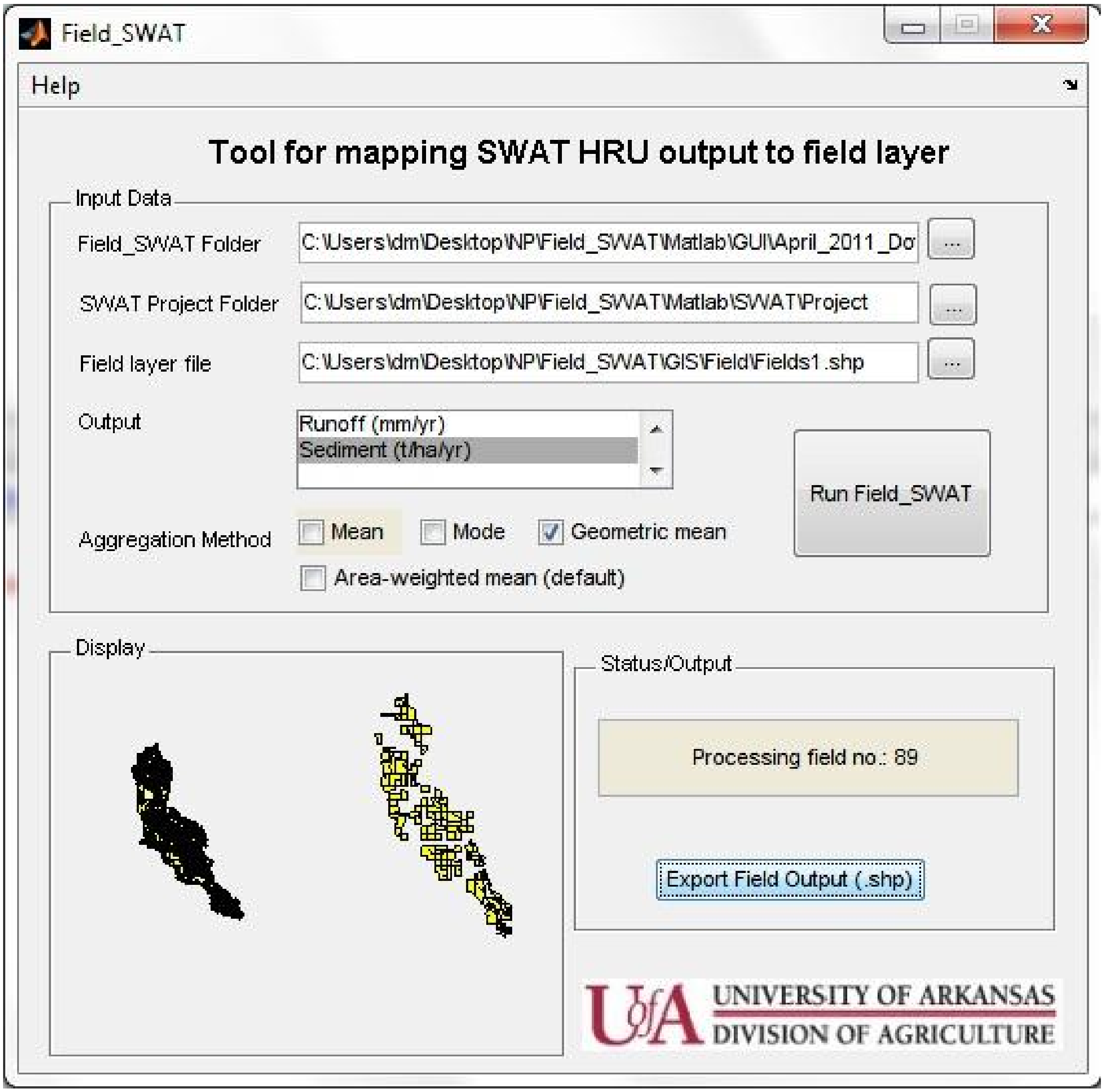

Figure 4.2: Field_SWAT interface for implementation of mapping algorithm.

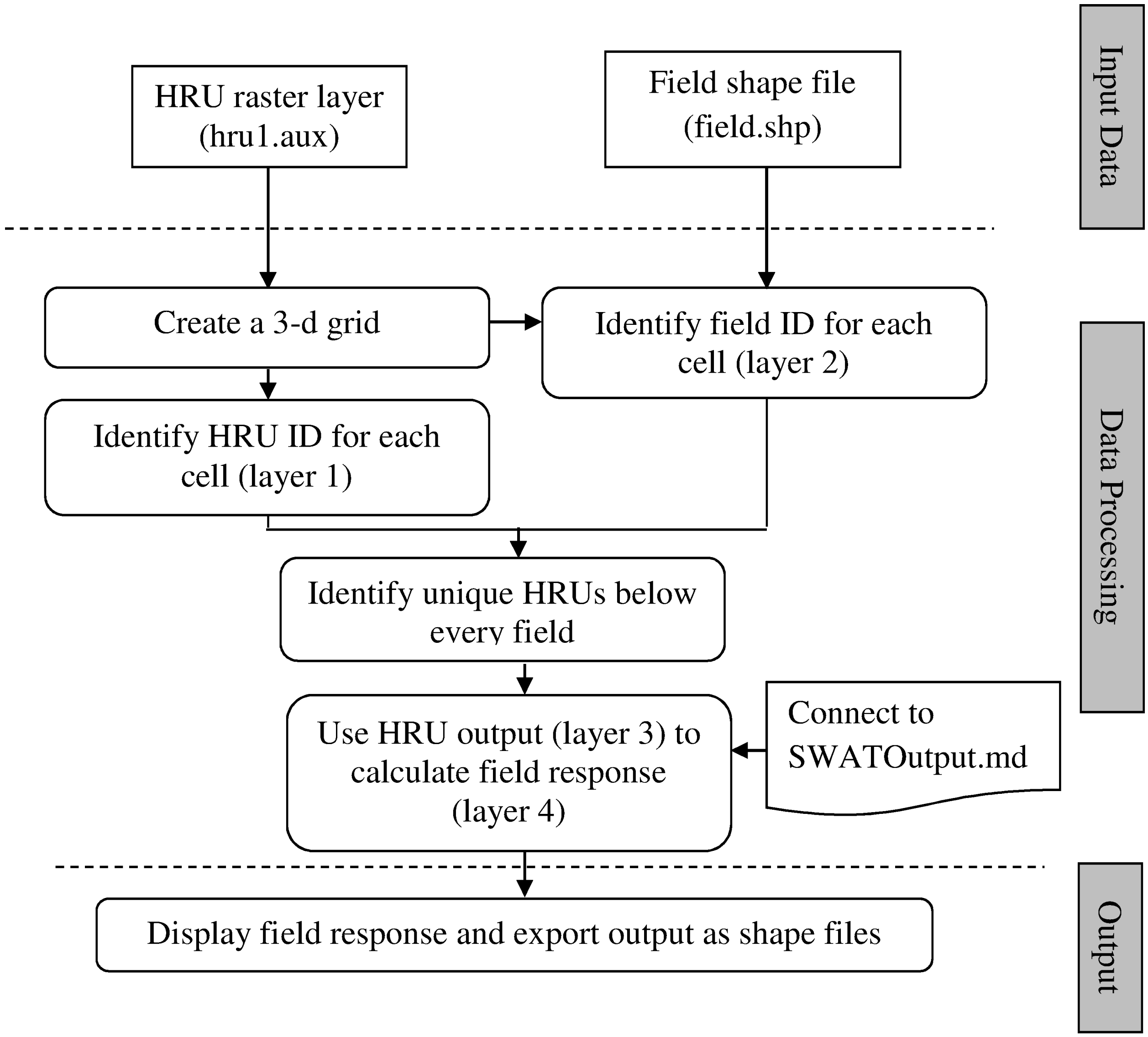

Figure 4.3: Flowchart showing the functioning of the Field_SWAT tool.

values while watershed level information in layers (z-axis) as and when the data become available during Field_SWAT setup. As mentioned previously, the grid file (hru1.tif) created by GDAL has the HRU ID information embedded for each cell which is read by Field_SWAT and stored in the first layer of z axis (fig. 4.3 and 4.4).

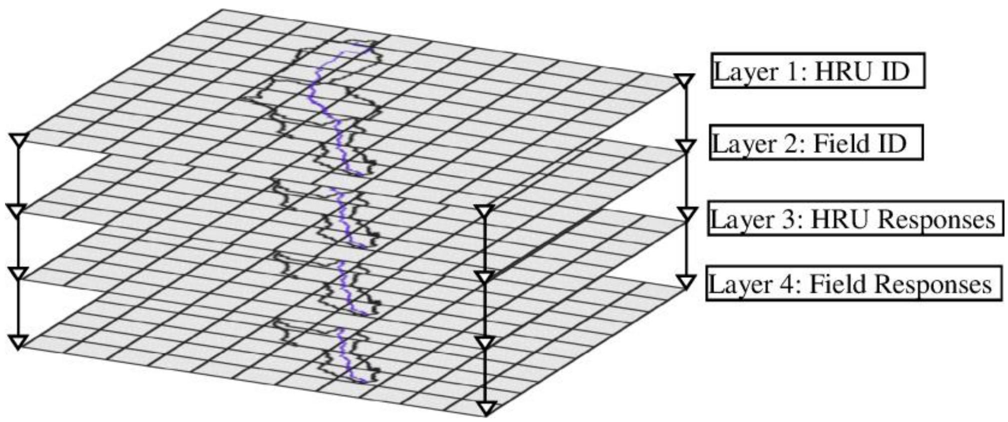

Figure 4.4: llustration of the Field_SWAT grid used to store various watershed level information.

The second task performed by the tool upon selection of the SWAT project folder is to copy the HRU vector shapefile created by SWAT in its Watershed\Shapes folder to Field_SWATs Shape folder. This file is later used to display the HRU level outputs from the SWAT model in the display for comparison with field level output.

The next input required by Field_SWAT is the field boundary layer, which is required as a polygon vector shapefile format (say, field.shp; fig. 4.3). Typically, this may be developed by user either by manually tracing the boundaries in GIS software using an aerial image as basemap or by collecting corner coordinates of the field using a global positioning system. This layer may represent one or more fields in the watershed with a unique ID for each field. The extent of each field must be equal to or greater than the cell resolution of the HRU layer; otherwise a default of zero loading is assigned. Field_SWAT reads this polygon layer to identify individual field boundaries. To convert this vector-based information into Field_SWAT's grid based information, every element in the grid is uniquely associated with an overlying field ID using an algorithm developed by Hormann and Agathos (2001) that is incorporated in the INPOLYGON function in

MATLAB. These field IDs are stored in Field_SWAT grids' second layer (fig. 4.3 and 4.4). This completes the input data requirement for Field_SWAT.

Subsequently, the user is required to select one of the two outputs (annual runoff or sediment) for which this tool is designed and click on the Run Field_SWAT button. The algorithm then connects to the SWATs output database (SWATOutput.mdb) stored in Scenarios\Default\TablesOut folder and extracts the annual runoff or sediment yield (based on users choice) for each HRU and stores it in the third layer of the Field_SWAT grid (fig. 4.3 and 4.4). The mapping between HRU (first layer) and field (second layer), is used to identify all HRUs that fall under a particular field. All HRUs used to calculate field output and their minimum and maximum loading information are stored in the Output folder for any post-processing.

To calculate the pollutant loading from each field, a spatial aggregation method is required to map the HRU output to field output. The tool provides users with four options including mean, model, geometric mean, and area-weighted mean to perform the spatial aggregation. The results, based on the chosen method of data aggregation, are displayed in the display panel of Field_SWAT. The tool also lets the user export the results in the form of a shapefile, stored in its Output folder, for developing custom maps in a GIS environment or for further analysis.

4.3.4 Test Run

To demonstrate the working of the above algorithm, the SWAT model (ArcSWAT 2.1.4 interface and SWAT 2005 algorithm) was setup for the agriculturally dominated Second Creek watershed (189 km^2) in Arkansas (fig. 4.5). This is a subwatershed of the 8-digit hydrological unit code (HUC) L'Anguille River Watershed (HUC 08020205). The Second Creek flows in the northwest southeast direction through the Woodruff and Cross Counties before it drains into the L'Anguille River near Palestine in the St. Francis County. The 12-digit HUC subwatersheds starting from north are Upper Second Creek (USC), Middle Second Creek (MSC), and Lower Second Creek (LSC). The watershed terrain is flat with about 95% of the drainage area in the 0-3% slope category. The overall land cover of the watershed is primarily row crop agriculture (66.9%) followed by forest (22.2%). However, USC and MSC have about 78.5% and 84.5% agricultural areas, respectively, making this watershed a suitable candidate to test this field-scale mapping algorithm.

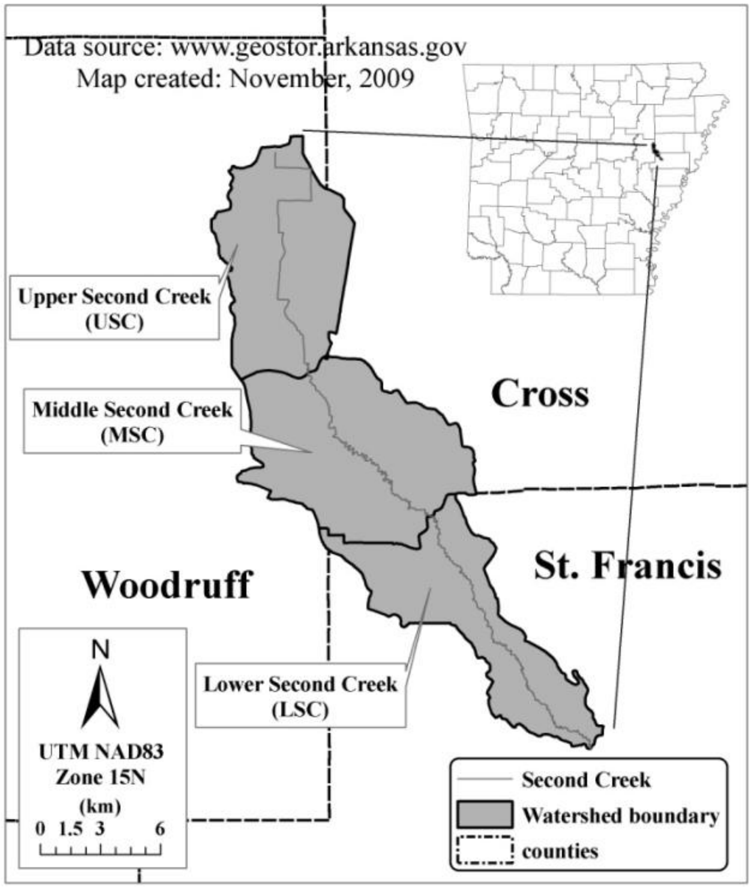

Figure 4.5: Second Creek watershed boundary showing the major creek and location of the watershed within Arkansas.

Key inputs to the SWAT model were the digital elevation model (30 m resolution), NHD high resolution flowline stream layer (1:250,000 scale), LULC (Fall 2006; 28.5 m resolution), and soil survey geographic (SSURGO) soil map. The subwatershed boundary was delineated using the 12-digit HUC watershed boundary using the user-defined watershed delineation option in ArcSWAT. The HRUs were delineated without applying any thresholding for the LULC, soil, and slope categories. This resulted in 218 HRUs, which had a minimum, maximum, mean, and standard deviation of 0.0001 km^2, 24.9 km^2, 0.86 km^2, and 2.66 km^2, respectively. Historical daily precipitation and temperature information was incorporated in the model using a national weather service weather gage data at Beedeville (COOP ID, 030536, lat/lon, 35°28'N/91°03'W, elev, 73.2

m) and was assigned to each subwatershed. Other weather parameters such as wind speed, solar radiation, and relative humidity were simulated by the model using its internal weather generator. The model was run on an annual scale from 1992 to 1999. No attempts were made to calibrate the model since the focus of this project was implementing and evaluating the functionality of the mapping algorithm. The Field_SWAT tool was run using a field layer GIS shapefile that had 89 polygons representing arbitrarily selected fields and other land parcels in the test watershed. Note that the field layer was manually delineated in a GIS environment using aerial imagery as basemap.

The performance of the tool and effect of spatial aggregation method was evaluated by statistically comparing the histograms of annual runoff and sediment yield for SWAT HRU and Field_SWAT results and visually observing the effects of spatial aggregation. Finally, the standalone nature of this tool was tested on computers that did not have MATLAB environment installed on them.

4.4 Results and Discussions

The Field_SWAT tool was used for mapping SWAT HRU results for the Second Creek watershed. The Field_SWAT grid for this watershed, similar to SWAT's HRU layer, consisted of 1023 rows and 655 columns resulting in 670,065 grid points with 30 m cells. The 30 m cells in the HRU layer resulted from the use of 30 m DEM that was used while developing the SWAT model. We also verified that areas of HRU calculated from Field_SWAT were comparable to the areas reported by HRU_FR variable in the HRU files (.hru) and with areas calculated from hru1.shp in ArcMap, both of which are developed while setting up the SWAT model.

4.4.1 Statistical Comparison

The means and standard deviations of the annual runoff and sediment provided in table 4.2 summarize the statistical changes through various aggregation methods. The statistics for HRU output were calculated using only those HRUs that contributed to the 89 fields in the field layer. In general, it was observed that spatial aggregation resulted in increasing the means and reducing the standard deviations. The mean runoff increased from 3.4% to 19.5% while sediment yield mean increased from 4.0% to 22.0% depending on the choice of aggregation method. On contrary, the standard deviations decreased from 36.1% to 57.4% for runoff and 51.8% to 66.1% for sediment yield depending on the aggregation method. This was expected because any spatial aggregation method typically reduces the low frequency values at both ends of a histogram (Isaaks and Srivastava, 1989; Bian and Butler, 1999). Consequently, we expect the mean to shift slightly on the higher side. This effect can be clearly seen in figures 4.6 and 4.7. Application of aggregation methods resulted in taller and tighter distributions. Based on results in table 4.2 and figures 4.8 and 4.9, it appears that either mean or area-weighted mean aggregation method would be a suitable choice for visualizing field outputs for the Second Creek watershed because their means tend to be closer to that of original dataset. However, since this tool is expected to assist watershed managers with spatial field-level targeting, it was important that the aggregation method also produced a visually consistent field output.

Table 4.2: Statistical summary of HRU and field-scale annual runoff and sediment outputs.

Output Scale	**Aggregation method**	**Runoff (mm)**		**Sediment (t/ha)**	
		Average	**Std. Dev.**	**Average**	**Std. Dev.**
HRU	none	262	122	5.0	5.6
Field	mean	271	52	5.4	1.9
	mode	313	78	6.1	2.7
	geometric mean	293	66	5.9	2.3
	area-weighted mean	296	66	5.2	2.6

4.4.2 Visual Comparison

Field_SWAT outputs were visually compared with the HRU level runoff and sediment yield output using color-coded maps (fig. 4.8 and 4.9). In deciding the range of responses to be used for color-coding these maps, we arbitrarily selected four equal intervals. The Field_SWAT software was run four times to test the four spatial aggregation methods. Each aggregation method produced slightly different results when compared with the original HRU output. The mean and geometric mean aggregation methods resulted in smoothing of the original data. This was particularly evident

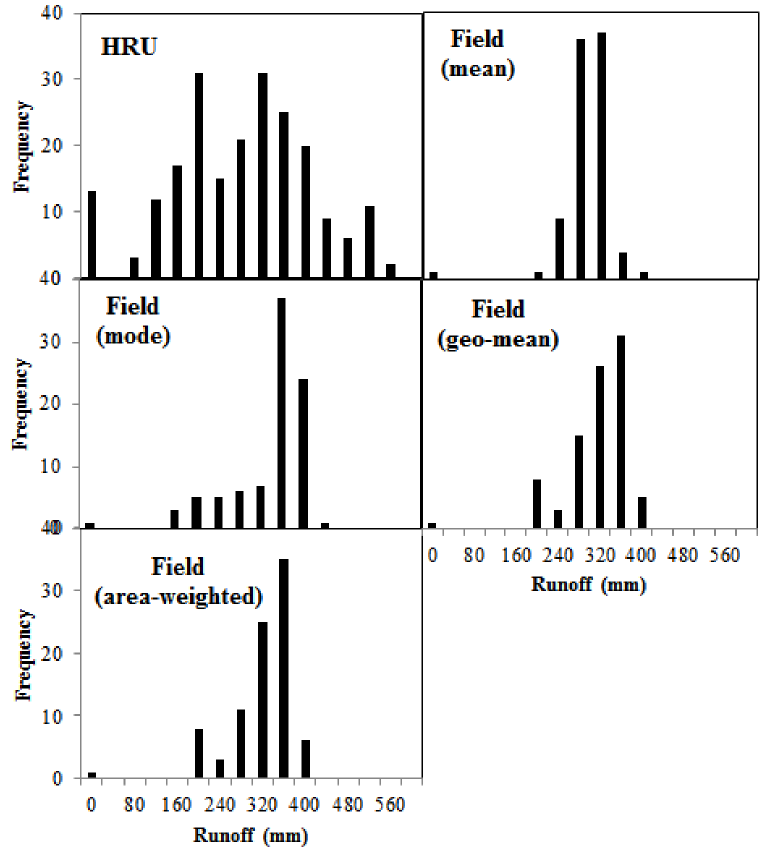

Figure 4.6: Histogram of the SWAT HRU and Field_SWAT runoff output using various aggregation methods.

during sediment mapping (fig. 4.9), where most fields in the northern and central portions of the watershed were mapped as green because of presence of the grey (0.0 - 2.6 t/ha) and yellow (7.3 - 15.6 t/ha) sediment yield classes in the original map. On contrary, the area-weighted mean produced a more spatially consistent map when the HRU and Field_SWAT outputs were visually compared. This was because the area-weighted method normalizes the contribution of each HRU based on its area within the field.

Based on statistical and visual observations, the area-weighted method was most suitable for mapping the HRU output to fields for the Second Creek watershed. For field-level targeting, area-weighted map showed several fields in the middle second creek subwatershed having above average sediment loading (fig. 4.9). These fields could be subjected to further on-site verification or targeting conservation practice. It is also interesting, however, to observe that mapping using the mode

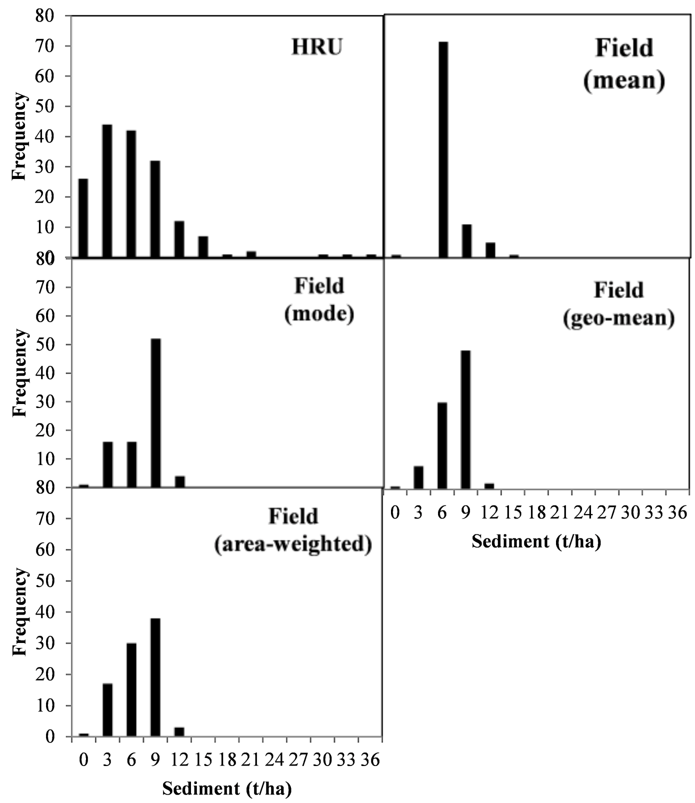

Figure 4.7: Histogram of the SWAT HRU and Field_SWAT sediment output using various aggregation methods.

method preserved the one of the highest runoff-yielding field in the central part of the watershed while all other methods tended to smooth the output for this field (fig. 4.8). Fields such as this may be of interest to someone who is targeting potential higher runoff areas in the watershed for conservation practice. Availability of multiple aggregation methods provides Field_SWAT users with the flexibility of rapidly mapping HRU outputs using various methods.

To further evaluate the effect of area-weighted averaging, we visually compared the HRU and Field_SWAT sediment yields at a finer spatial scale in an area, which had a combination of rice and soybean fields along with some forested areas (fig. 4.10). In general, it was observed that HRU sediment yield varied even within a field, which is not the case for Field_SWAT results. Field_SWAT results are concentrated in nature, align to the boundaries of the field, and hence, provide a clear visualization of model responses. Forested areas fell in the green (0.00 5.00 t/ha)

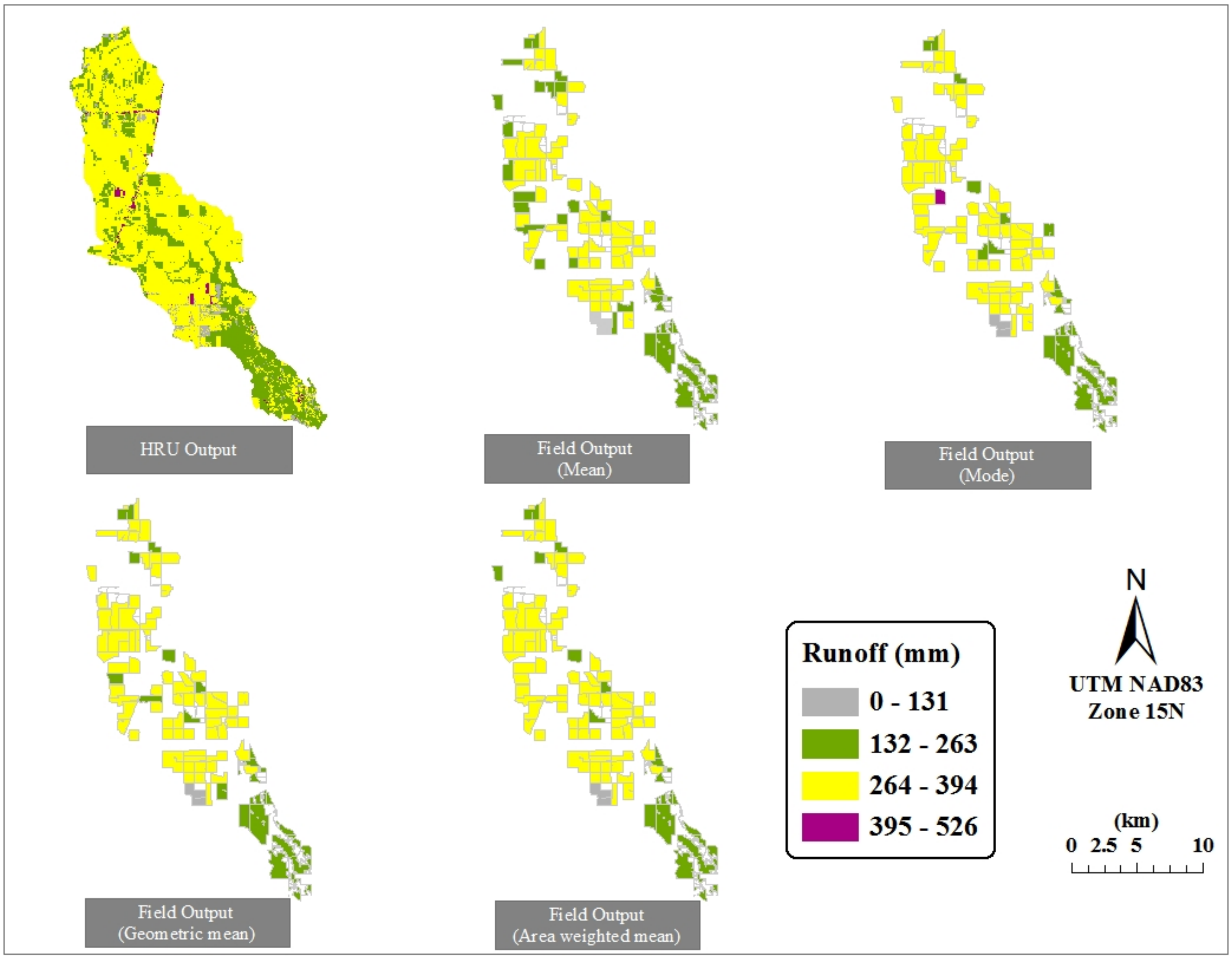

Figure 4.8: Comparison of annual runoff from SWAT HRU and field-scale output using various spatial aggregation methods.

category of sediment yield in the HRUs, which was transferred exactly in Field_SWAT mapping results. The effect of area-weighted averaging was prominent in some agricultural fields, and resulted in the intermediate category of sediment yield of encompassed HRUs being applied to the field when three or more categories were present. For instance, the soybean field on the top right corner (labeled 1 in fig. 4.10a) had a combination of green (0.0 5.00 t/ha), some yellow (5.01 8.7 t/ha), and red (>8.7 t/ha) sediment yield categories in SWAT's HRU results (fig. 4.10b). This was mapped as the intermediate yellow category in Field_SWAT results (fig. 4.10c). Similar effects can be seen for other agricultural fields in fig. 4.10. Results like these can be used by watershed managers to identify suite of conservation practices for fields that contribute greatly to watershed pollution.

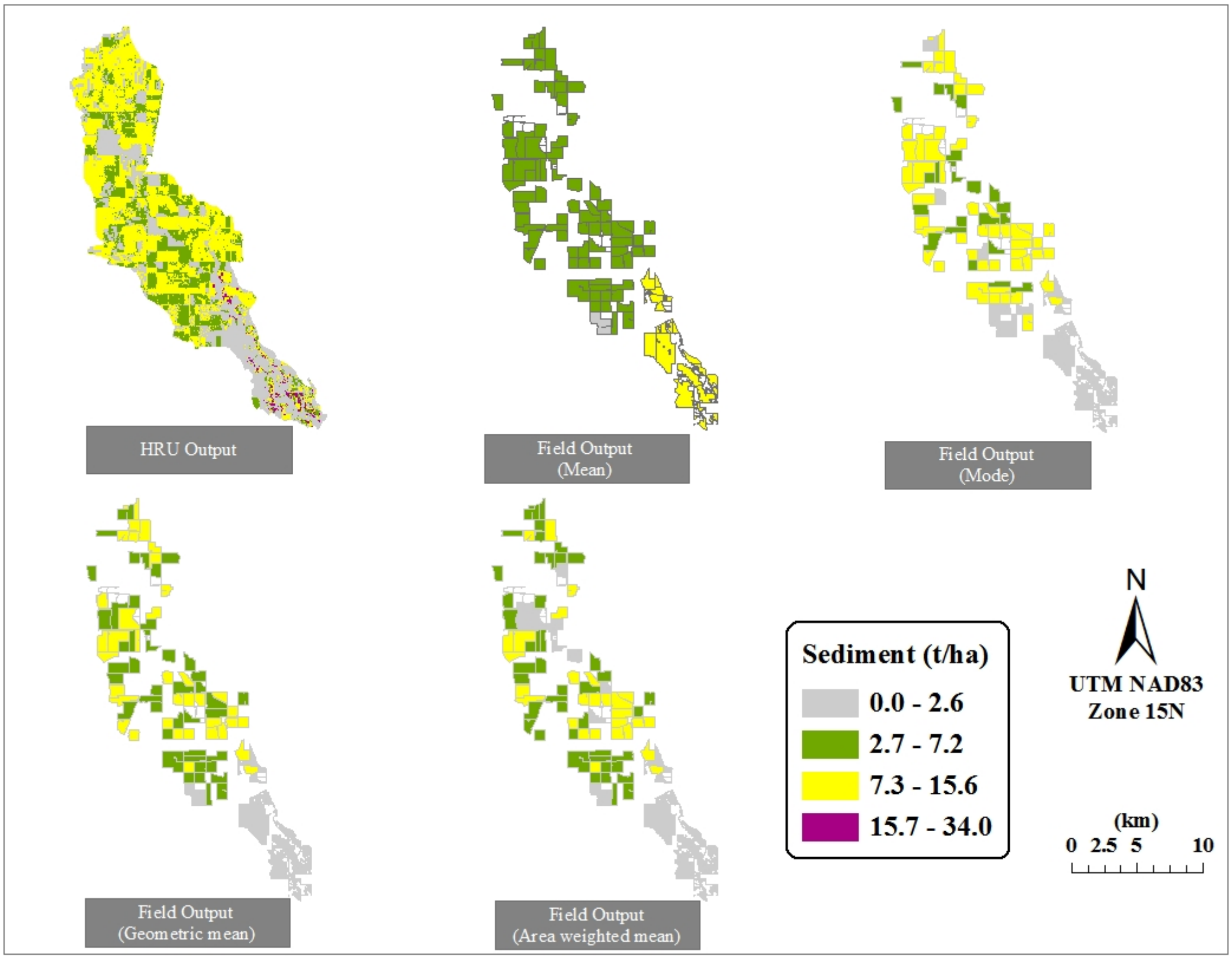

Figure 4.9: Comparison of annual sediment yield from SWAT HRU and field-scale output using various spatial aggregation methods.

Although the SWAT model was initially developed as a river basin scale model, it has been recently used for field scale runoff (Anand et al., 2007), sediment, and nutrients (Gollamudi et al., 2007) assessment studies. In these studies, the model was setup for individual fields by using the field edges as the watershed boundary while field scale monitoring data was used for calibration and validation. Veith et al. (2005) setup the SWAT model for a 39.5 ha watershed consisting of about 22 fields and used the phosphorous (P) loadings from HRUs to validate the Pennsylvania P-index, a simple measure used to assess field vulnerability to P losses. They concluded that the SWAT model better represented natural processes at field scale and its complexity made it a favorable choice for P-index calculations. Overall, it appears from recent literature that there is a concerted effort to use and improve the SWAT model results at field scale. We envision that the

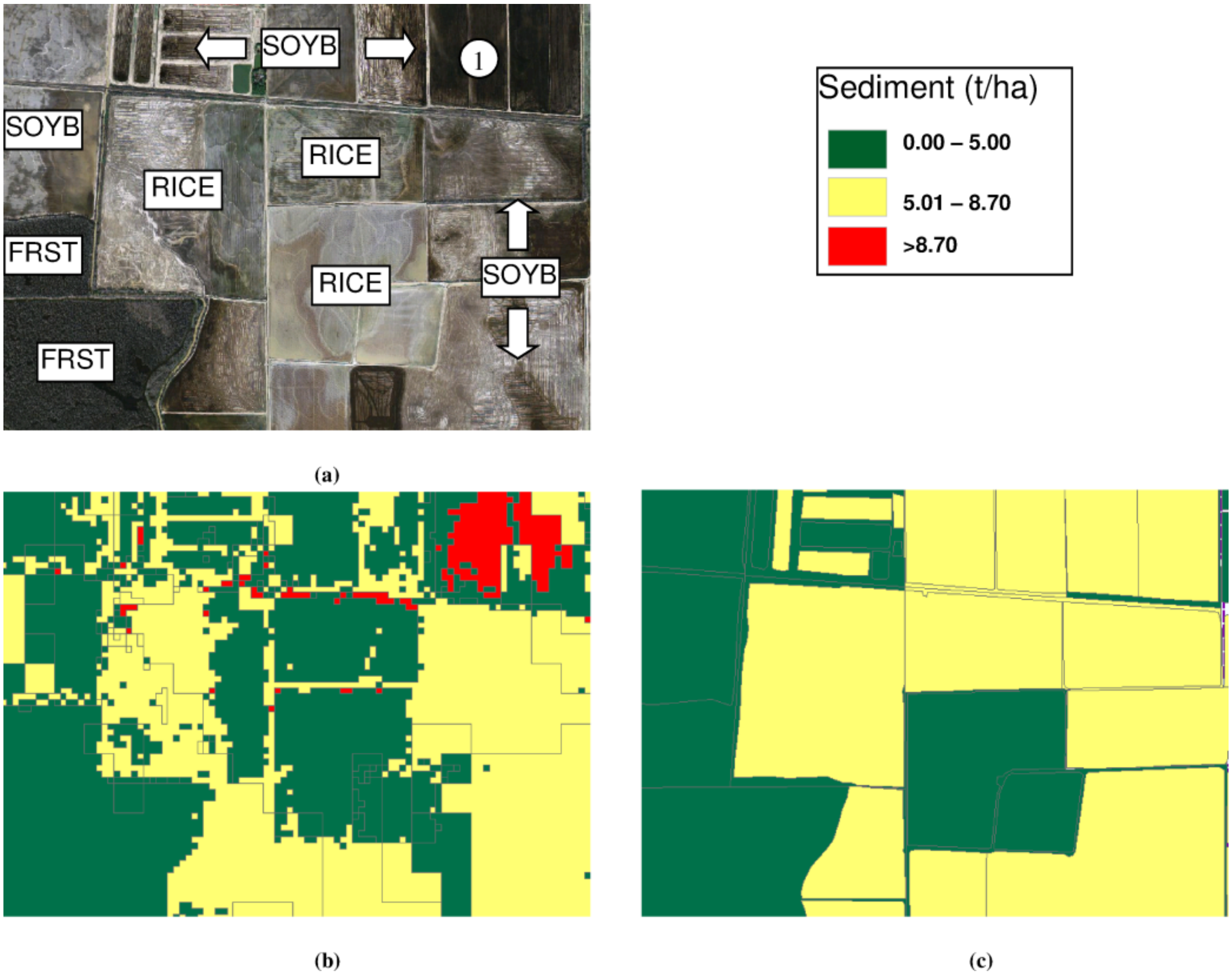

Figure 4.10: Comparison of SWAT HRU and Field_SWAT results at a lower spatial scale. (a) Aerial imagery of an area showing combination of forest (FRST), rice (RICE), and soybean (SOYB) landcovers, (b) SWAT HRU output for sediment yield, and (c) Field_SWAT sediment yield output.

development of Field_SWAT mapping algorithm and its implementation as a stand-alone software program will facilitate the use and further investigation of SWATs field-scale abilities. No attempt was made in this study to validate field responses, as the focus of the study was to develop a visualization tool. A thorough testing of this tool will require edge-of-the-field water quality data and that will be addressed in future efforts.

4.4.3 Software Performance

The Field_SWAT software package (algorithm and supporting libraries) occupies about 233 MB of computer memory (hard disk space). To use any software that is developed in MATLAB, the end user should have a set of supporting libraries called the MATLAB compiler runtime (MCR) installed on the computer. This freely available library (230 MB) is packaged with the Field_SWAT software and must be installed before starting the Field_SWAT tool. Please note that this is a one-time install for any tool developed in MATLAB. We tested the software on a computer on which MATLAB was not present to verify its stand-alone capacity. On a desktop computer with Intel® Pentium® D CPU 3.40 GHz processor with 2 GB of random access memory (RAM), the install time for the MCR library was about six minutes. After the installation of the MCR library, the Field_SWAT tool took about one minute to get started while the mapping of 89 fields of Second Creek Watershed using any of the aggregation method took an additional minute.

4.5 Summary and Conclusions

The concept of HRU development is one of the least discussed aspects in SWAT model literature. This paper provides details of the HRU delineation process in the SWAT model using an example. In general, it was understood that HRUs are fragmented areas of land, which can be spatially located in a watershed but are not synchronous to any physical boundaries. We developed a user-driven stand-alone graphical user interface, called Field_SWAT, to map the HRU level annual runoff and sediment output from the SWAT model to a user-defined field boundary layer. Once a SWAT model is developed and satisfactorily calibrated and validated, the only requirement of this tool is a user-defined boundary layer. Four different methods - mean, mode, geometric mean, and area-weighted mean provide users with options for mapping HRU outputs using multiple spatial aggregation techniques. It must be stressed that this tool does not produce any new model simulation but simply transfers HRU output to user-defined field boundaries using one of the four spatial aggregation method. The tool was tested on the agriculturally dominated Second Creek watershed

SWAT model using a layer consisting of 89 fields. Based on statistical and visual results, it was observed that the abstract HRU outputs were best mapped to field outputs using the area-weighted aggregation method. Considering that the SWAT HRU results are now being used to identify critical nonpoint source pollution areas in the watershed (White et al., 2009), this tool can be used for field-level targeting and enhancing communication between SWAT modelers and watershed managers/stakeholders.

Acknowledgements

The authors would like to thank the Center for Advanced Spatial Technology (CAST) at the University of Arkansas for providing the computing resources for this research project. The final version of this paper benefited significantly from the comments and suggestions made by the associate editor and an anonymous reviewer.

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Chapter 5

Summary and Recommendations

5.1 Synthesis of Chapter Contents

The overall goal of this research was to develop geospatial tools and techniques to support specific aspects of watershed management. Land-use change impacts (Chapter 2), subwatershed priority allocation (Chapter 3), and field-scale output visualization (Chapter 4) are some of the aspects of watershed management that were addressed using approaches based on the SWAT model. The tools/techniques developed in this research are generic and can be applied to any watershed with different land-uses, soil types, topography, and climate. However, specific study areas were chosen based on the suitability of the application and availability of necessary input data. The following sections outline objectives and key results from each chapter.

5.1.1 Chapter 2

The objectives of Chapter 2 were to evaluate the sensitivity of the SWAT 2009 model to concurrent land-use changes, and develop an automated tool to allow SWAT modelers to incorporate multiple land-uses during simulation. The results from this study demonstrated the advantages of the new LUC module in SWAT 2009. Model responses were studied with and without the LUC module activated for the urbanizing Illinois River Drainage Area in Arkansas (IRDAA) watershed. Depending on the subwatershed, the urban areas increased by 2% to 22% during the study period, this resulted in over prediction of groundwater by up to 15%, when the LUC model was not activated. In addition, a single post-development LULC layer over predicted the surface runoff for most subwatersheds. In summary, activation of the LUC module is expected to result in improved temporal and spatial hydrological responses at the subwatershed scale.

The results also provided SWAT modelers with a novel computer-based geospatial tool, titled

SWAT2009_LUC, to prepare input files required to activate the LUC module in SWAT 2009. Results from application to the IRDAA SWAT model showed that the tool was able to produce LUC module input files that successfully and accurately changed the land use three times during the model run period. Once the tool ingests the necessary input datasets and information, the time required for development of these files was only about 5 min. Because the LUC module input is data intensive, this tool can encourage modelers to quickly verify if incorporating land use changes enhances their models' predictive abilities.

5.1.2 Chapter 3

The objectives of Chapter 3 were to develop a modeling approach for prioritizing 12-digit hydrologic unit code (HUC) subwatersheds based on sediment, total phosphorus (TP), and nitrate-nitrogen (NO_3-N) contributions, and corroborate the resulting priorities using surrogate datasets. To develop the prioritization methodology, the SWAT model was setup for the IRDAA watershed. The subwatershed boundaries were established using the predefined 12-digit HUC boundary layer. Major spatial datasets included were soil, hydrography, elevation, precipitation, and land use maps. Temporal data inputs included effluent discharge from wastewater treatment plants, multi-year land use maps, precipitation, and detailed land management data.

A combination of sensitivity analysis and literature review was used to identify key calibration parameters. Calibrated output involved total flow, surface flow, base flow, sediment, TP, and NO_3-N. The model was calibrated and validated at seven locations for hydrology and three locations for water quality outputs, first at annual scale and then at monthly scale. A multi-objective function consisting of percent relative error (RE), Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), coefficient of determination (R^2), and ratio of the root mean square error to the standard deviation of measured data (RSR) were used to guide model evaluations. The model outputs were generally found to be satisfactory or better and within ranges reported in previous SWAT publications.

The average annual flow-weighted concentrations were used to prioritize 12-digit subwatersheds based on their individual contributions of sediment, TP, and NO_3-N. The priority subwatersheds comprised only 24% of the total area of the IRDAA watershed but contributed 49% of sediments, 33% of TP, and 27% of NO_3-N annual average loads. Linkages between subwatershed characteristics and water quality were established, which served as surrogates for rapidly validating the priority watersheds. In general, the highest priority subwatersheds based on the constituent of interest were found to be associated with urban and pasture land uses, while the subwatersheds' slope and soil hydrologic groups seemed to explain some high priorities. The lowest priority subwatersheds in general were found to be associated with high forest and low urban land-use dominated subwatersheds, with no evidence of association with the subwatersheds' slopes and soil hydrologic groups. Known water quality impairments also served to validate the priority watersheds. Selecting these subwatersheds ahead of others for planning and rehabilitation activities can justify the use of limited resources.

5.1.3 Chapter 4

The objective of Chapter 4 was to develop a methodology to map HRU outputs from the SWAT model to field boundaries to understand field-scale impacts and simplify communication of outputs to stakeholders. This objective was realized in the form a stand-alone user-friendly geospatial tool titled Field_SWAT, which uses output from the SWAT model and maps it to user-defined field boundaries. The tool was applied for mapping the SWAT models annual runoff and sediment outputs from 218 HRUs to 89 individual field boundaries in an agriculturally dominated watershed in Northeast Arkansas. Field outputs from the tool were compared using four different spatial aggregation methods mean, mode, geometric mean, and area-weighted mean. The results showed that area-weighted spatial aggregation method resulted in most suitable mapping of field-scale output. The research demonstrated that the Field_SWAT could be a useful tool for field-scale targeting of conservation practices and enhancing communication between SWAT modelers and watershed managers/stakeholders.

5.2 Future Directions

Although the studies described above provided methodologies to support specific watershed management applications, during the course of this research, interesting work opportunities were identified that could serve as research avenues for future studies.

1. Chapter 2 provided a method to change the distribution of land uses in the SWAT model during simulations by modifying the HRU area. However, only existing HRU areas can be changed using this method. New land-uses in a sub-watershed cannot be represented currently within the SWAT model. Future work is required, specifically with the SWAT model algorithm, so that it can include new land-uses when such information becomes available so that land-use change impacts can be simulated.

2. In Chapter 2, model simulations were compared between a single LULC layer and three LULC layers, to quantify the sensitivity of the SWAT model output to changing land uses. The results from this study suggested that the finer temporal resolution of LULC is better than coarser resolution. With these results, however, comes the research question "How many LULC maps are required to adequately capture the impacts of land use changes?" To answer this question, future studies are required that compare the SWAT model simulations resulting from multi-temporal LULC datasets to provide guidelines for the optimal temporal LULC resolution in a watershed.

3. The Field_SWAT tool developed in Chapter 4 provides a method to map the HRU output to user-defined field boundaries. No attempt was made in this study to validate field responses, as the focus of the study was to develop a visualization tool. Future work is required to validate Field_SWAT output with edge-of-the-field water quality data to gain more confidence in the maps.

4. In addition, the Field_SWAT tool can currently map results only for annual runoff and sediment. Future development of this tool can involve other outputs such nutrient loss, which

are important in agricultural watersheds.

Chapter 6

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