APPLICATION OF SWAT FOR IMPACT ANALYSIS OF SUBSURFACE DRAINAGE ON STREAMFLOWS IN A SNOW DOMINATED WATERSHED

A Thesis
Submitted to The Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

Mohammed Mizanur Rahman

In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Agricultural and Biosystems Engineering

November 2011

Fargo, North Dakota

North Dakota State University
Graduate School

Title

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

ABSTRACT

Rahman, Mohammed Mizanur, M.S., Department of Agricultural and Biosystems Engineering, College of Engineering and Architecture, North Dakota State University, November 2011. Application of SWAT for Impact Analysis of Subsurface Drainage on Streamflows in a Snow Dominated Watershed. Major Professor: Dr. Zhulu Lin.

The wet weather pattern since the early 1990's has created two problems for the people living in the Red River Valley (RRV): (1) wet field conditions for farmers and (2) more frequent major spring floods in the Red River system. Farmers in the region are increasingly adopting subsurface drainage practice to remove excess water from their fields to mitigate the first problem. However, it is not clear whether subsurface drainage will deteriorate or mitigate the spring flood situation, the second problem.

The Soil and Water Assessment Tool (SWAT) model was applied to evaluate the impacts of tile drainage on the Red River's streamflows. The model was calibrated and validated against monthly streamflows at the watershed scale and against daily tile flows at the field scale. The locations and areas of the existing and potential tile drained (PTD) areas were identified using a GIS based decision tree classification method.

The existing and maximum PTD areas were found to be about 0.75 and 17.40% of the basin area, respectively. At the field scale, the range of Nash-Sutcliffe efficiency (NSE) for model calibration and validation was 0.34-0.63. At the watershed scale, the model showed satisfactory performance in simulating monthly streamflows with NSE ranging from 0.69 to 0.99, except that the model under-predicted the highest spring flood peak flows in three years.

The results of modeling a 100% tiled experimental field showed that about 30-40% of water yield was produced as tile flow. Surface runoff and soil water content decreased about 34% and 19%, respectively, due to tile drainage. However, the impact of subsurface drainage on evapotranspiration (ET) and water yield was mixed. ET slightly decreased in a wet year and slightly increased in a dry year, while the pattern for water yield was opposite to that of ET. The watershed-scaled modeling results showed that a tiling rate of 0.75-5.70% would not have significant effects on the monthly average streamflows in the Red River at Fargo. For the 17.40% tiling rate, the streamflow in the Red River at Fargo might increase up to 1% in April and about 2% in fall (September to November), while decreasing up to 5% in the remaining months.

This SWAT modeling study helped to better understand the impact of subsurface drainage on the water balance and streamflows in the Red River of the North basin. The findings will also help watershed managers in making decisions for the purpose of managing agricultural drainage development in the RRV and other snow dominated watersheds around the world.

ACKNOWLEDGEMENTS

I would like to express my gratitude to those people who helped me to accomplish this research work. It would not have been possible to reach this final stage of my degree without their scholarly contributions in improving this research.

Firstly, I would like to thank my major adviser, Dr. Zhulu Lin, who ushered me towards the hydrological modeling study at the very beginning of my NDSU life when I was an infant in this field. Since then his prudent mentorship, scholarly expertise and patience have been helping me to mold myself as an independent researcher.

I would like to thank my committee members, Dr. Dean D. Steele, Dr. Xinhua Jia and Dr. Tom DeSutter, for their valuable suggestions and comments to standardize my research throughout the two year tenure of my master's study. Special thanks to Dr. Xinhua Jia for sharing her own research data, otherwise, this present study would have suffered an incompleteness indeed.

I would like to show my gratefulness to Dr. D. N. Moriasi for providing programming code and to Dr. Thomas Scherer and Ms. Roxanne M. Johnson for sharing their field experiences in my work. I also express my thankfulness to the departmental staff Ms. Jana Daeuber, Ms. Lori Buckhouse, Ms. Nancy Stroh and Ms. Melanie Ziegler for their nice cooperation.

Heartiest thanks to my friends Mr. Md. Atikur Rahman, Mr. Ewumbua Menyoli Monono, Mr. Vinay Gonela, and Mr. Niteen Jadhav for encouraging me all times.

Last but not least, I would like to thank my family members for their tireless support.

DEDICATION

To my friends Mr. Md. Khorshed Alam, Mr. Sahiduzzaman Sarker and Ms. Afroza Ayesha.

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1. INTRODUCTION

The Red River of the North Basin (RRNB) has been in a wet weather pattern since early 90s (Novotny and Stefan, 2007; Pates, 2011). As a result, farmers in the Red River Valley (RRV) have been experiencing wetter than normal working conditions and increasing soil salinity problems in their lands. Installation of subsurface (or tile) drainage systems helps to remove excess water to improve field conditions, to alleviate salinity problems, and to increase crop yield. Since more and more farmers in the RRV are adopting tile drainage practices, field tiling is becoming a burgeoning business in the region. It is estimated that the percentage of tiled fields in the RRV has increased from nearly nonexistent to about 7% during the same time period and the number is increasing (Pates, 2011). According to a report prepared by the North Dakota State Water Commission (NDSWC), about 40% of the area laid on glacial aquifer along the western part of the Red River has the potential to be tiled (Schuh, 2008).

When the farmers in the RRV are experiencing wetter field conditions, the residents along the rivers in the RRNB have also witnessed more and more frequent major spring floods. For example, in the century-long stream stage history, five out of the ten highest historic crests in the Red River at Fargo occurred in the past 15 years (Koehler, 2010). Therefore, a question often asked is whether the increasingly adopted tile drainage agricultural water management practices will further increase the chances of spring flood in the area or will mitigate the spring flood situation? The Red River Retention Authority formed the Basin Technical and Scientific Advisory Committee (BTSAC) to investigate the potential impact of tile drainage on peak streamflows and subsequently to provide scientific and technical advice for the purpose of managing agricultural drainage development in the RRV (BTSAC, 2011). It is believed that subsurface drainage systems normally promote drainage from the waterlogged root zone of agricultural lands and consequently increase water yield (Moriasi et al., 2007; Sugg, 2007; Sands et al., 2008). On the other hand, it is also argued that tiling in this region would reduce water yield during spring snowmelt time by holding more snowmelt water for a longer period of time in previously (in fall) tile drained, dry soils (Luick, 2011).

These arguments are mainly based on the scientific evidence supported by field scale studies that were conducted in different regions and under various climatic conditions (Gowsami et al., 2008; Sands et al., 2008). It is less well known how the subsurface drainage will affect the land-phase hydrology and more importantly the streamflows in the RRNB from a watershed-scaled perspective (Sands, 2001). It has been shown that, for a tile drained watershed having a high groundwater table like in the RRNB, subsurface flow (tile flow and/or base flow) will significantly influence streamflows in terms of peak flow, time to peak, and flow volume (Sands et al., 2008; Kiesel et al., 2010). Therefore, it is important to study the potential impact of tile drainage on streamflows in the RRNB through watershed hydrologic modeling.

The Soil and Water Assessment Tool (SWAT), a continuous, physically–based, semi-distributed, watershed model developed by USDA-ARS (Arnold et al., 1993), has been successfully used to assess the impacts of land use and climate change on streamflows at the basin and watershed scales throughout the world, including in cold regions (Benaman et al., 2005; Wang and Melesse, 2005; Srivastava et al., 2006; Ahl et al., 2008;

Chaponniere et al., 2008; Sexton, 2010). This model has been used through GIS (Geographic Information Systems) interfaces, e.g., ArcSWAT and MWSWAT. In recent years, SWAT's applications can also be seen in tile drained watersheds, especially in the USA (Du et al., 2005; Green et al., 2006; Sui and Frankenberger, 2007). Although the present tile drainage algorithm of SWAT (ArcSWAT2009) is based on a simple exponential equation requiring four parameters, it still gives reasonable results reported in the references cited above. However, the reliability of this algorithm should not be judged on the basis of the past few studies. Some ignored important parameters, for example, spacing of tile lines, size, drainage coefficient of soils need to be considered in the tile drainage algorithm if more reliable simulations are desired (Moriasi et al., 2007). Though DRAINMOD (Skaggs, 1978) is a reliable model for tile flow simulation and considers all important parameters associated with tile drainage, its use is yet limited for the field scale modeling. An on-going area of research is trying to incorporate the Hooghoudt-Kirkham tile drainage algorithm, adopted in DRAINMOD (Skaggs, 1978), into the SWAT model (Daniel Moriasi, 2011, personal communication; see also Moriasi et al., 2007). It is reasonable to assume that the SWAT model, with a more reliable tile drainage algorithm, will have a greater applicability to analyze the impacts of tile drainage on quantitative and qualitative hydrology at the watershed scale. Other commonly used hydrologic and water quality models with tile drainage algorithms also include Root Zone Water Quality Model (RZWQM; USDA-ARS, 1992), Agricultural Drainage and Pesticide Transport model (ADAPT; Alexander, 1988), and CoupModel (Jansson and Karlberg, 2011), but their applications are limited to field scale.

One of major obstacles for modeling tile drainage flow with SWAT is the difficulty to accurately identify the existing tile drained areas within the watershed of interest because there is no reliable database of the existing tile drained areas for USA (Sugg, 2007). In recent years, several methods based on GIS and remote sensing techniques have been proposed to map tile drained areas (Suggs, 2007; Naz and Bowling, 2008; see also the discussions in the Literature Review Section). However, none of these tile mapping approaches has been applied in hydrologic simulation with SWAT. The purpose of the study is to apply SWAT to analyze the impact of the subsurface drainage on the streamflows in the Upper Red River of the North Basin (URRNB) which drains at Fargo. The specific objectives of this study include:

(i) To develop the SWAT model for simulating the streamflows in the Upper Red River of the North basin;

(ii) To map the existing tile drained areas in the URRNB using a GIS-based decision tree classification method;

(iii) To conduct scenario analyses of the impacts of tile drainage on streamflows in the URRNB.

2. REVIEW OF LITERATURE

Existence of tile drains overlying a shallow aquifer can imbalance the seasonal hydrology. In such an environment, subsurface drainage will be the principal competitor of surface runoff if the topography of the land surface is flat. Studies have shown that tile flow could reduce as much as 70% of surface flow by allowing more precipitated water to be infiltrated into soils (Green et al., 2006). Numerous modeling studies have been done previously to understand how subsurface drainage flow influences water balance of land phase hydrology and which water balance components are sensitive to tile flow (Jin and Sands, 2003; Du et al., 2005; Helmers et al., 2005; Luo et al., 2008). This section is aimed at providing a review for past research studies on subsurface drainage modeling at the watershed scale.

2.1. Effect of subsurface drainage on watershed water balance

Comprehensive field studies on how tile drained flow affects the water balance components of watershed are hardly seen, because measuring all components at the watershed scale is impractical. To some extent, the nature of redistribution of water among land phase hydrologic components due to tile installation may be explained by physically based models. Du et al. (2005) conducted a modeling experiment with modified SWAT (SWAT-M) in the Walnut Creek watershed (Iowa) where 74% of total area was tile drained. They found that the contribution of surface runoff, tile flow, and baseflow to average annual streamflow were about 30, 33 and 37 %, respectively. These results were thought to be reliable as the associated errors were reduced adequately by calibrating this model against measured streamflow and actual evapotranspiration (ET). Later, Green et al. (2006) applied the same model in the South Fork watershed of Iowa where about 80% of land was tile drained. When the SWAT-M was tested with and without tile drainage conditions, it was shown that including the tile drainage in the model improved the streamflow predictions by decreasing average annual surface runoff and ET by about 68 and 11%, respectively. These findings revealed that significantly less surface runoff would be generated in the intensely tile drained watersheds located in Midwest USA.

The amount of discharge at tile outlets is affected by many factors along the air-soil-tile drain route traveled by the infiltrated water. The dominant factors include rainfall characteristics, land use, soil properties, size, and the arrangement of tile lines. Tile drainage responds rapidly and proportionally to rainfall during early cropping stage when ET demand is low. But during the vegetative stage when ET demand is higher, tile flow is small (Tom Scherer, 2011, personal communication; see also Randall and Mulla, 2001; Jin and Sands, 2003; Helmers et al., 2005; Luo et al., 2008; Kiesel et al., 2010). In a field experiment in Minnesota, Sands et al. (2008) found that on average 82% of tile drainage water flowed in April-June and 9% in July-October. If the preceding cropping season experiences a drought, then in the following spring a major portion of snowmelt water will replenish the dry soils. In this situation the yielded subsurface drainage flow will be comparatively less (Sands et al., 2008).

In cold climates, soil temperature is an important factor affecting tile flow through the freeze-thaw thawing processes. When air temperature rises in early spring, snowpack (if present) will be melting first leaving less heat available to be transferred into soil, which will delay the thawing of the frozen soil and limit infiltration (Mitchell and Warrilow, 1987). In another study Baker (1997) showed that in early spring snowmelt water often refroze at the interface of snowpack and soil surface; and consequently infiltration was obstructed. However, some studies showed that even though snow was present, infiltration occurred immediately after snowmelt because the soils were not frozen near the surface (Cherkauer and Lettenmaier, 1999; Pitman et al., 1999). Iwata et al. (2010) showed that thicker snowpack resulted in thinner frozen soils and thinner snowpack resulted in thicker frozen soils. They concluded that thick frozen soils impeded infiltration and produced more spring surface runoff whereas thinner frozen soils comparatively produced less surface runoff. Therefore, in snow dominated areas, soil temperature should be taken into consideration in hydrologic modeling. When modeling five watersheds in Canada during the winter season, Belanger et al. (2009) showed that SWAT simulated lower soil temperature than observed and that the lag coefficient of soil temperature equation adopted in SWAT had greater influence on soil temperature in the deeper layers than in the surface layers.

The timing of peak flow has the same of importance as the discharge of peak flow in watershed assessment and flood analysis. How rapidly tile flow will be seen at an outlet mostly depends on the soil drainage properties (Du et al., 2005; Kiesel et al., 2010). From a controlled field experiment in two watersheds in Illinois, Gowsami et al. (2008) showed that about 77% of the tile drained water flowed during recession period of hydrograph and therefore, it should reduce peak flows in receiving streams. The conjecture is that after a rainfall, the previously much deeper groundwater table took a longer time to reach above tile lines and thus the tile flow lagged behind peak streamflow.

2.2. Subsurface drainage algorithms and models

Many models with different subsurface drainage algorithms have been developed in the past to simulate tile drainage flow. In the following paragraphs, some commonly used models (field or watershed scale) having tile algorithms are discussed with regard to their relative advantages and disadvantages.

The DRAINMOD model (Skaggs, 1978) is widely used in field-scale subsurface drainage modeling and the tile drainage algorithm used in DRAINMOD has been incorporated into several popular models like the Chemicals, Runoff, Erosion from Agricultural Management Systems (CREAMS; Knisel, 1980; Parsons and Skaggs, 1988; Wright et al., 1992; Saleh et al., 1994), the Groundwater Loading Effects of Agricultural Management Systems (GLEAMS; Leonard et al., 1987; Knisel, 1993; Thooko et al., 1994), and the Root Zone Water Quality Model (RZWQM; Ahuja and Hebson, 1992). DRAINMOD (Skaggs, 1978) uses a modified Green-Ampt equation to estimate infiltration and the Hooghoudt equation (Hooghoudt, 1940) to estimate tile drainage flux. If the water table is at the ground surface then Kirkham's steady state flow equation (Kirkham, 1957) is used to estimate drainage flow rate. The required inputs are hourly rainfall, maximum and minimum air temperature, crop, and soil data. Over the last 30 years DRAINMOD has been improved significantly. One of the latest versions, DRAINMOD 5.1, can model the processes of snowmelt, and freezing and thawing of soil moisture in cold environments (Luo et al., 2000). This latest DRAINMOD model was found to be effective in Canada (Dayyani et al., 2009), but less effective in simulating peak flow in Illinois (Christopher and Cooke, 2003). Christopher and Cooke (2003) also suggested that DRAINMOD5.1 needs more attention in regards to modifying its temperature parameters. Northcott et al. (2002) integrated DRAINMOD with GIS software to be used at the watershed scale and tested the GIS-interfaced model in the Upper Little Vermilion River watershed in east-central Illinois. The model was successful in estimating tiled flow but was not recommended for total hydrology simulation at the watershed scale because of its over-sensitivity to saturated soil hydraulic conductivity (Parsons et al., 2001) and an inefficient ET module (Northcott et al., 2002; Dai et al., 2010). Sammons et al. (2005) also indicated that the Green-Ampt equation of DRAINMOD ignored land use effects on infiltration.

The Agricultural Drainage and Pesticide Transport Model (ADAPT), developed by Alexander (1988), is a field scale drainage model. Although both DRAINMOD and ADAPT models use Hooghoudt and Kirkhams's equations for tile flow, ADAPT uses the Soil Conservation Service-Curve Number (SCS-CN) method for infiltration, and the energy balance method for snowmelt hydrology. Sands et al. (2003) found that ADAPT underestimated tile drainage flow during snowmelt periods but gives good results during periods of rainfall.

The Root Zone Water Quality Model (RZWQM), a lumped field scale model, was developed by USDA-ARS in the 1990's to simulate the physical, chemical, and biological processes in cropped fields. The Green-Ampt equation is used to model infiltration and the Hooghoudt equation is used for tile flow simulation. Generally, RZWQM was found to be able to predict subsurface drainage flow (Johnsen et al., 1995; Kumar et al., 1998a, and b; Bakhsh et al., 1999). This model also considers macropore's effect on the field water balance (Singh et al., 1996; Kumar et al. 1998b; Bakhsh et al., 1999). However, Abrahamson et al. (2005) reported that the calibrated RZWQM model did not show significant differences in simulated tile flow when modeling with and without considering macropore's effect. In modeling a river basin in Canada, Ahmed et al. (2007) found that the RZWQM was not able to simulate streamflows fed by spring snowmelt very well. It is also worth mentioning that a GIS-based interface was also developed for RZWQM (Wang and Cui, 2004).

An earlier version of SWAT estimated tile flow using the following equation:

$$\mathrm{tile}_{\mathrm{wtr}} = (\mathrm{SW} - \mathrm{FC})\left(1 - \exp\left[\frac{-24}{\mathrm{tile}_{\mathrm{drain}}}\right]\right) \quad \text{if SW} > \text{FC} \tag{2.1}$$

where $\mathrm{tile}_{\mathrm{wtr}}$ is the tile drained water from soil profile; SW is soil water content, FC is field capacity, and $\mathrm{tile}_{\mathrm{drain}}$ is the time to drain to FC of soil. These variables are expressed on a daily basis and units are in mm. In equation (2.1), it is hypothesized that if soil water exceeds field capacity for a given soil layer, then tile flow will occur. However, whether a tile drain will have any drainage flux or not also depends on the relative position of the water table and the tile drain. The current SWAT version (SWAT2009) uses the modified form of equation (2.1) (Neitsch et al., 2009):

$$tile_{wtr} = \left(\frac{\mathrm{h}_{\mathrm{wtbl}} - \mathrm{h}_{\mathrm{drain}}}{\mathrm{h}_{\mathrm{wtbl}}}\right)(\mathrm{SW} - \mathrm{FC})\left(1 - \exp\left[\frac{-24}{\mathrm{tile}_{\mathrm{drain}}}\right]\right) \quad \text{if } \mathrm{h}_{\mathrm{wtbl}} > \mathrm{h}_{\mathrm{drain}} \tag{2.2}$$

where $\mathrm{h}_{\mathrm{wtbl}}$ and $\mathrm{h}_{\mathrm{drain}}$ are height of water table (mm) and tile drains (mm) above an impervious layer, respectively. Ignoring tile line spacing, perhaps, is one of the major drawbacks of equation (2.2). The current SWAT'S tile algorithm was found to be less effective compared to DRAINMOD when a significant amount of modeling area was covered by tile drains (Chikhaoui et al., 2010). The present SWAT's tile module can be replaced by the Hooghoudt and Kirkham's subsurface drainage equations to enhance

SWAT's capability in modeling tile drainage. Moriasi et al. (2007) has incorporated these equations into SWAT and has showed improved model performance.

In SWAT, the tile flow is estimated either at the entire basin level if it is completely under tile drained or at the Hydrologic Response Unit (HRU) level if the basin is partially tile drained. An HRU is a unique combination of soil, land use and slope within each subbasin, which, in turn, is a smaller unit of the entire basin. For a partially tile drained basin, SWAT requires spatial location of tile drained areas.

2.3. Mapping tile drained areas

In the Midwest region of the USA, a significant amount of agricultural land is drained by subsurface drainage systems as natural drainage is impaired by fine textured soils, flat topography, and high ground water tables (Sugg, 2007). However, there is often a lack of information about the tile drained areas and the characteristics of the tile drainage systems (Sogbedji and McIsaac, 2002; Ruark et al., 2009). Although the National Resource Inventory (NRI) had surveyed tile drained areas along with surface drained areas in 1992, the dataset was not recommended for use because the dataset was outdated and was based on remote sensing imagery and aerial photographs without any physical validation (Sugg, 2007). Neither the State Soil Geographic database (STATSGO) nor the Soil Survey Geographic database (SSURGO), developed by NRCS, has incorporated tile drainage information (Sugg, 2007). Subsurface tile lines installed 50 or more years ago throughout the USA have no registry about their locations (Naz and Bowling, 2008).

At the field and small farm scales, the locations and areas of the tile drained fields have been identified by locating the outlets and vents of tile lines, analyzing crop symptoms, applying GPS (Global Positioning System) techniques (Ruark et al., 2009), and using ground penetrating radar technologies (Allred et al., 2004). However, these approaches will no longer be practical for a watershed of which a large portion is tiled. Instead, GIS-based and remote sensing methods are recommended for such a purpose (Sugg, 2007; Naz and Bowling, 2008). Sugg (2007) identified the tile drained area by overlaying row crops data from the National Land Cover Dataset 1992 (NLCD 1992) and poorly drained soil data of STATSGO in a GIS environment for eighteen leading subsurface drainage States. This method is called soil drainage class (SDC), which assumes that the tile drainage systems have been or will be potentially installed in areas where crops cannot grow or are less productive due to high ground water table in poorly drained soils. The SDC method produced good agreement for heavily tile drained states (e.g., Ohio, Iowa, and Illinois); but produced an inferior agreement for those less heavily tiled areas (Arkansas, Mississippi, Missouri, Louisiana, and Red River Valley of the North). Although surface slope information was not used in the SDC method, Sugg (2007) recommended the inclusion of slope information for more realistic results.

Similar approaches to Sugg (2007) were applied to estimate the potential tiled area in the North Dakota side of the RRV (Schuh, 2008), in which soil and aquifer properties rather than land use information were used. In the first approach, USDA aquic soil was assumed to be an indicator of the potential tile drainage areas as this soil represents the properties of a shallow groundwater table. In the second approach, if any of the three drainage soils such as very poorly, poorly and somewhat poorly drained in SSURGO overlays a shallow aquifer; then the corresponding area was considered suitable for subsurface drainage. Both methods showed that about 35-40% of the North Dakota RRV could be tile drained.

To identify the location of a tile drainage area, Kiesel et al. (2010) used a probability method. In this method, potential grid cells with high possibility for tile drainage were first selected by overlaying soil and topographic spatial data. Then, a probability function of subsurface drainage was developed based on the existing subsurface drainage data. Finally, the estimated tile drained area was obtained by multiplying the potential grid cells with the probability function. The authors applied the above technique with SWAT modeling and found this approach should not be used in watersheds where no sufficient quantitative information about existing tile drainage is available to develop a reliable probability function.

Remotely sensed data, either from aircraft or from satellite, are thought as one of the promising alternatives to identifying individual tile lines (Verma et al., 1996; Northcott et al., 2000; Varner et al., 2002). The accuracy of remote sensing is greatly affected by the types of electromagnetic spectrum and their reflectivity from the earth's surface. The degree of this reflectance depends on soil moisture, texture, organic matter, and tillage practices. In principle, the soils above or close to the tile lines will dry faster than surrounding soils; and consequently, the dried soils will reflect more spectrum leaving a lighter color in the resultant imagery. On the basis of this principle, Verma et al. (1996) successfully delineated tile line locations for an area of 259 hectares using color infrared aerial photographs. They suggested that optimal results could be achieved if images were taken after 2 or 3 days of a 2.54 cm rainfall event. However, the presence of organic matter in soils may make soils wetter, thus false tile lines may be identified along moist soils (Jensen, 2000).

Naz and Bowling (2008) also applied GIS and image processing techniques to identify tile lines from aerial photographs in Tippecanoe County, Indiana. The potential tile drained area, where the possibility of being tiled is high, was identified by overlaying land use, soil, and surface slope data in a GIS environment using the decision tree classification approach. Subsequently, an aerial image of the potential areas was processed to refine the locations of the tile lines. However, they found that this image processing approach was rather limited: (1) other features like roads and field boundaries appeared like tile lines in aerial photographs and could cause an overestimation of the actual tiled areas;(2) in a harvested area where crop residues were still left in the field the low spectral resolution pixels of aerial image could not be used to differentiate between dry soils and crop residues (Baird and Baret, 1997; Daughtry, 2001; Streck et al., 2002; Varner et al. 2002).

The research studies discussed in this chapter have highlighted the influence of tile drainage on different water balance components of hydrology mostly at field scale whereas few studies have focused at watershed scale. However, a distinct study on how tile drainage can impact on seasonal peak streamflows has not yet been conducted at watershed scale. Moreover, identification of scattered tiled field is one of the major limitations in hydrological modeling at watershed scale. The present study was conducted to bridge the aforesaid gaps in perspective of the URRNB.

3. MATERIALS AND METHODS

3.1. Soil and Water Assessment Tool (SWAT) model

The GIS based SWAT model, ArcSWAT2009 (Neitsch et al., 2009), was used in this study. To set up a SWAT model three primary GIS data layers are required: (1) topography of the watershed, commonly known as digital elevation model (DEM), (2) land use/land cover, and (3) soils. SWAT divides a watershed into the number of subbasins based on DEM, and for each subbasin a stream is created by the principle of flow accumulation and direction. The model further divides a subbasin into smaller model units known as hydrologic response unit (HRU), from the information of land use, soil, and surface slope. Each HRU is homogeneous with respect to these three variables. This special feature allows SWAT to account for spatial variation within a watershed and to take less computing time. The outlet location of the delineated watershed is defined by the user to compare observed streamflow with modeled streamflow.

SWAT divides the hydrology of a watershed into two major phases. The first phase is the estimation of different hydrologic components at the HRU level and then the amount of respective hydrologic component generated by all HRUs within a subbasin are summed to get a total load for that subbasin. This phase determines how much water will be available for streamflow in each subbasin and this total water is called water yield (figure 3.1 and equation 3.1). The second phase is channel routing, which transfers the streamflow generated by each subbasin to the watershed outlet through channel networks. The major hydrological components are precipitation, surface runoff flow, abstraction by pond/ wetland, percolation, groundwater flow from shallow aquifer, lateral flow, tile drainage flow, evapotranspiration, soil moisture storage, and flow to deep aquifers. If there is any impermeable layer with sufficient gradient towards a stream between the groundwater table and the root zone then lateral flow occurs. If an HRU is assigned as tile drained, SWAT will estimate the corresponding tile flow using the relevant properties of that HRU. This generated tile flow is treated as lateral flow and ultimately it contributes to streamflow or potholes (if applicable). The accuracy of tile flow simulation depends on how precisely the user can identify the specific HRUs where tile drains exist if the basin is partially tile drained.

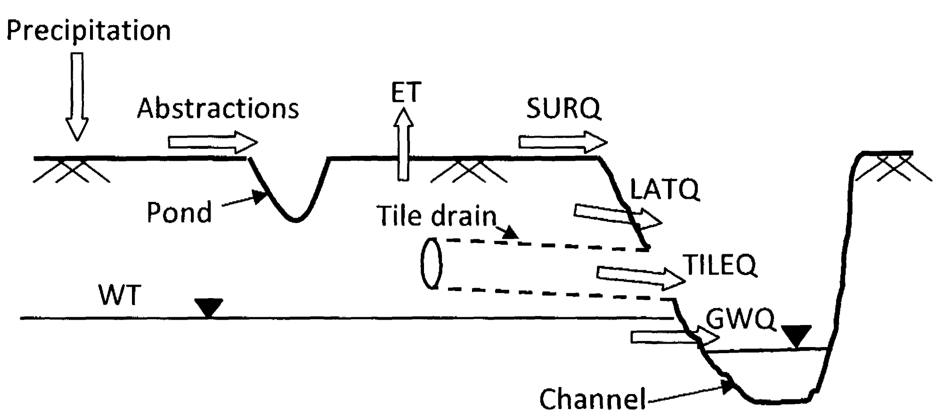


Figure 3.1. Components of water yield in SWAT (WT- Groundwater water table, ET – Evapotranspiration, SURQ – Surface runoff, LATQ – Lateral flow, TILEQ – Tile flow, and GWQ – Groundwater flow).

Water yield is expressed as the following equation,

$$\mathrm{WYLD} = \mathrm{SURQ} + \mathrm{GWQ} + \mathrm{LATQ} + \mathrm{TILEQ} - \mathrm{TLOSS} - \text{Pond abstraction} \quad (3.1)$$

where TLOSS is transmission loss through the bed of tributary channel i.e., net surface runoff contribution to the main channel and other terms have already been discussed.

Observed weather data are required for the model. If the Hargreaves method is used to estimate evapotranspiration (ET) then only daily precipitation and temperature data are to be provided. On the basis of ambient temperature SWAT determines whether precipitation will be treated as rainfall or snowfall which in turn accumulates as snowpack. Snowpack may melt or sublimate according to air temperature, and this melted snow is reconsidered as rainfall to the soil. The SWAT's snowmelt algorithm is a function of air temperature, snowpack temperature, snow melting rate, and areal coverage of snow. SWAT also estimates daily soil temperature to increase the reliability of the SWAT model to be used in the cold climate region where subsurface hydrology is influenced by soil temperature. The amount of snowmelt is estimated by

$$SNO_{mlt} = b_{mlt} \cdot SNO_{cov} \left[\frac{T_{snow}+T_{mx}}{2} - T_{mlt}\right] \quad (3.2)$$

where SNO_{mlt} is the amount of snowmelt (mm/d), b_{mlt} is the melt factor (mm/d-^{o}C), SNO_{cov} is the fraction of HRU area covered by snow, T_{snow} is the snowpack temperature (^{o}C), T_{mx} is the maximum air temperature (^{o}C), and T_{mlt} is the base temperature above which snow melt is allowed (^{o}C).

3.2. Tile drainage algorithms in SWAT

3.2.1. Simple tile drainage algorithm

The current SWAT version (SWAT2009) uses equation (2.2) to estimate daily drained water from the soil profile above the tile drain (Neitsch et al., 2009). The tile drained water estimated by equation (2.2) is then routed to the main channel (figure 3.1) by following equation.

$$Q_{tile} = Q_{tile} + Q_{tilestor,i-1}\left[1 - \exp\left(\frac{-1}{TT_{tile}}\right)\right] \quad (3.3)$$

where Q_{tile} is the amount tile flow (mm) discharging into the main channel on a given day, Q'_{tile} is the amount of tile flow (mm) generated from soil profile within a subbasin on a given day, $Q_{tilestor,i-1}$ is the amount of the lagged tile flow (mm) from the previous day and TT_{tile} is the travel time (days) of tile flow to reach the main channel.

The tile travel time (TT_{tile}) is calculated according to following equation:

$$TT_{tile} = \frac{tile_{lag}}{24} \quad (3.4)$$

where $tile_{lag}$ is the lag time (hours) for a tile drain.

3.2.2. Hooghoudt-Kirkham tile algorithm

The simple tile algorithm adopted by the current version of SWAT does not take into consideration spacing between the tile drains and size of the tile drains. Moriasi et al. (2007) recently incorporated the more robust Hooghoudt (1940) and Kirkham (1957) tile drain equations into the SWAT model. These two equations are also used in DRAINMOD model (Skaggs, 1978) to simulate subsurface drainage flow at the field scale. The relevant equations of the Hooghoudt and Kirkham algorithms are presented in the following paragraphs as described by Moriasi et al. (2007). The main assumption for the Hooghoudt and Kirkham algorithms is that tile flow will occur laterally when upper soil layer of tile drain is saturated. There are three conditions under which tile flow may occur.

<u>Condition-I:</u> If the groundwater table exists below soil surface (figure 3.2) and the depth of ponded water in surface depressions are less than the maximum depressional storage S_1 (figure 3.3) at which surface water can not directly contribute to tile drains,

then the following Hooghoudt (1940) steady-state equation will be used to estimate drainage flux.

$$q = \frac{8K_e d_e m + 4K_e m^2}{CL^2} \tag{3.5}$$

where q is drainage flux (mm/h), m is the midpoint water table height above the drain (mm), K_e is effective lateral hydraulic conductivity (mm/h), L is distance between drains (mm), C is the ratio of the average flux between the drains to the flux midway between the drains and is assumed to be unity (C=1) in this model, and d_e is equivalent depth substituted for d (height of the drain from the impervious layer) in order to correct for convergence near the drains (mm).

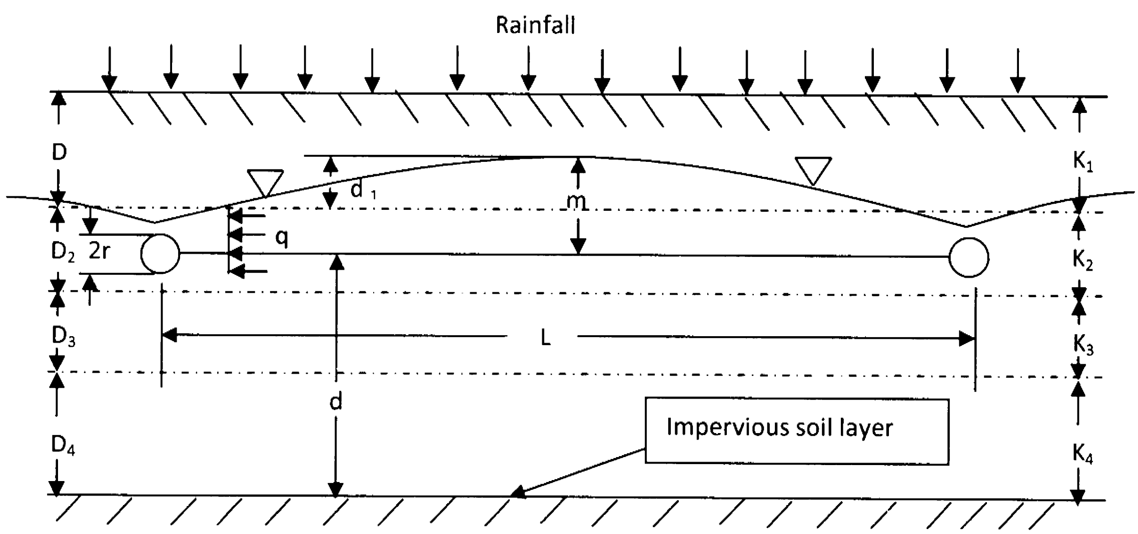


Figure 3.2. Schematic diagram of subsurface drainage system when water table exists below ground surface (Hooghoudt's equation).

The equivalent depth (d_e) is calculated by the Moody's (1966) equations:

$$d_e = \frac{D}{1+\frac{D}{L}\left\{\frac{8}{\pi}\ln\left(\frac{D}{r}\right)-\alpha\right\}} \quad \text{for } 0 \leq D/L \leq 0.31 \tag{3.6}$$

where D is the thickness of soil layer, and r is the radius of drain tube.

$$\text{Or, } d_e = \frac{L}{\frac{8}{\pi}\left\{\ln\left(\frac{L}{r}\right)-1.15\right\}} \quad \text{for } D/L > 0.31 \tag{3.7}$$

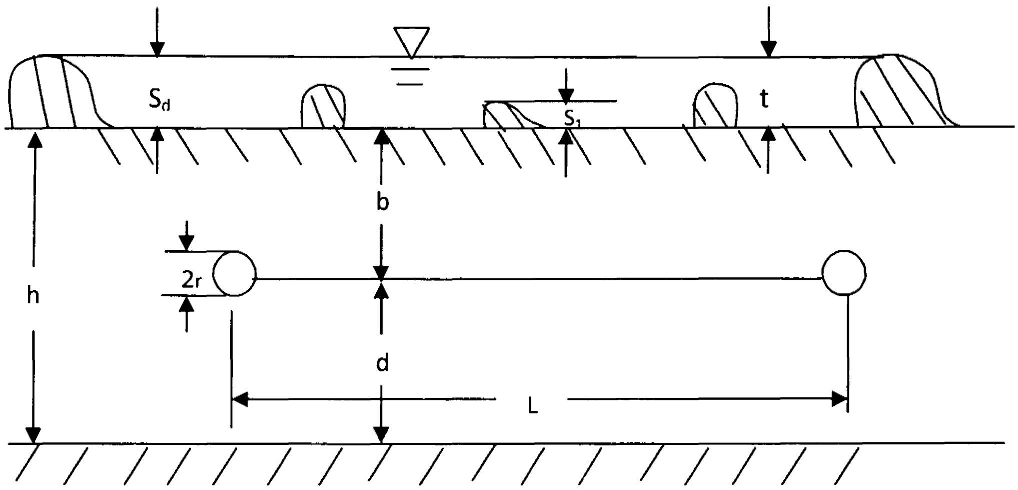


Figure 3.3. Schematic diagram of subsurface drainage system with a ponded surface.

For layered soils, composite horizontal hydraulic conductivity (K_e) will be calculated with the equation:

$$K_e = \frac{K_1 d_1 + K_2 D_2 + \ldots\ldots K_{n-1} D_{n-1} + K_n D_n}{d_1 + D_2 + \ldots\ldots D_{n-1} + D_n} \tag{3.8}$$

where d_1 is the depth of the saturated soil in the layer where water table intersects (figure 3.2). If the water table exists in the second layer (D_2), then d_1 will be zero and D_2 is denoted as d_2, and so forth.

Condition-II: If ponded depth in surface depression is greater than S_1 (figure 3.3) and water table rises over the ground surface and stays for a long time, then the Kirkham (1957) equation is used.

$$q = \frac{4\pi K_e (t+b-r)}{gL} \tag{3.9}$$

where t is the depth of ponded water, b is the depth from soil surface to the center line of the drain, and g is a dimensionless factor expressed as a function of d, L, actual depth of soil profile (h) and radius of tile tube (r). All linear dimensions are expressed in mm and K_e is expressed in mm/day.

Condition-III: If the estimated drainage flux by the above two equations is greater than the drainage coefficient (DC, mm/day), the flux (mm/day) will be equal to DC as expressed by the following equation.

$$q = DC \tag{3.10}$$

3.2.2.1. Maximum depressional storage (S_1 or S_d)

Maximum depressional storage (S_1 or S_d in cm) is calculated by the equation of Onstad (1984).

$$S_d = 0.112RR + 0.031RR^2 - 0.012RR * S \tag{3.11}$$

where RR is the random roughness (cm), and S is the slope of the land (%).The RR is a function of tillage, orientation of ridges, and weather where RR is taken from Saleh and Fryrear (1999).

$$RR = 0.1RR_i * e^{[DF(-0.0009CUMEI - 0.0007CUMR)]} \tag{3.12}$$

where RR (cm) is the random roughness at any time t (days) after a tillage operation, RR_i is the random roughness (mm) immediately after a tillage operation, CUMEI is cumulative rainfall erosivity (MJ mmha^{-1}h^{-1}), CUMR is cumulative rainfall (mm) since last tillage operation, and DF is decay factor estimated based on clay (%) (CLAY) and organic matter (OM) in the soils using the following equation.

$$DF = e^{[0.943 - 0.07CLAY + 0.0011CLAY^2 - 0.67OM + 0.12OM^2]} \tag{3.13}$$

3.3. Study area

The Upper Red River of the North Basin (URRNB) is situated at southeastern North Dakota and mid-western Minnesota. This basin drains into Red River of the North (RRN) at USGS stream gauge station 05054000 located at the City of Fargo, North Dakota (figure 3.4). Only about 7% of its total 16,500 square km drainage area is located within the State of South Dakota. The URRNB consists of five USGS 8-digit HUC's, namely, Mustinka River, Bois de Sioux River, Otter Tail River, Western Wild Rice River, and the Upper Red River.

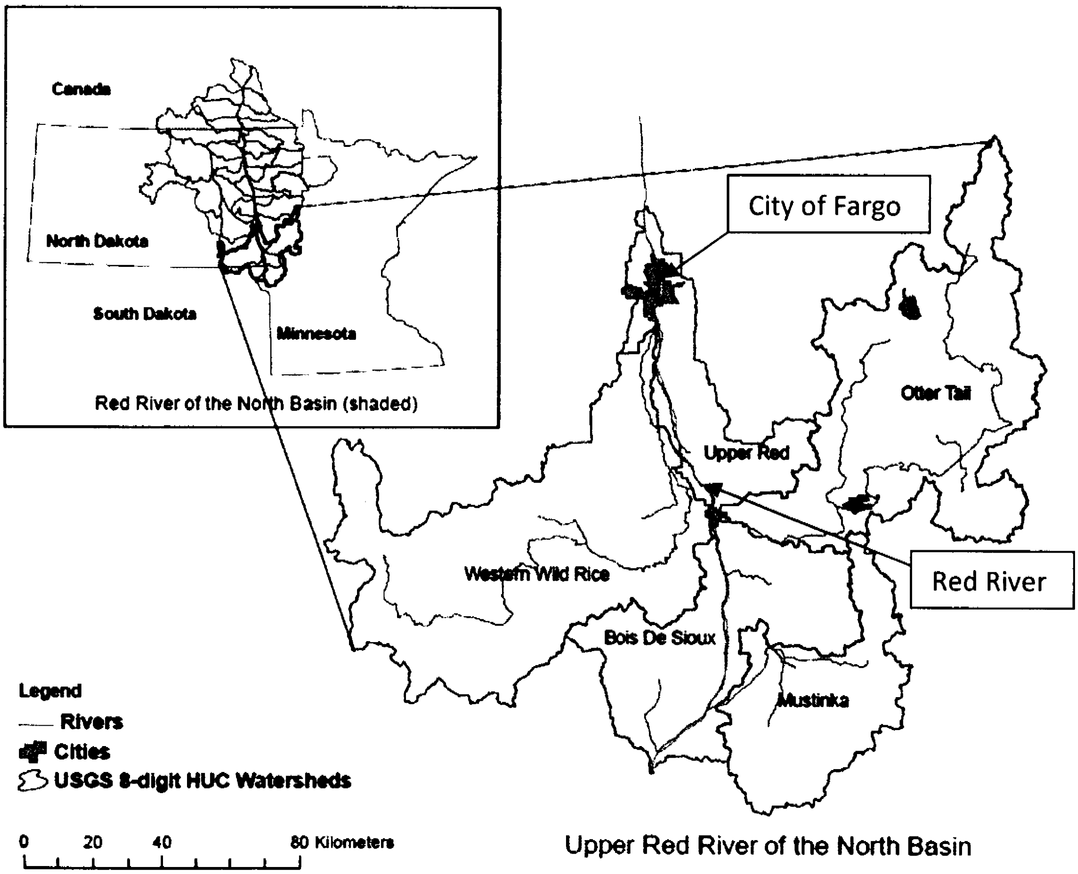


Figure 3.4. Geographical location of the Upper Red River of the North Basin (URRNB). Data sources: The National Hydrography Datasets and the North Dakota Geographic Information Systems database.

The topography of the basin is relatively flat except for the upstream portions of the Western Wild Rice River watershed and the Otter Tail River watershed. The major land uses in the URRNB are row crop agriculture (65%), followed by pasture/hay (11%), water/wetlands (10%), forest (9%), and urban (5%) (Lin et al., 2011). The hydrology of this region can be classified as snow hydrology during November through March; and rainfall hydrology during April through October. Mean annual precipitation varies from 510 to 560 mm and about 75% of the annual precipitation occurs from April through September.

3.4. Input data

3.4.1. DEM data

For this study, 10-m resolution DEM data were provided by the International Water Institute (2011). These DEM data were prepared using Light Detection And Ranging (LiDAR) approach under the Red River Basin Mapping Initiative.

3.4.2. River network

SWAT has two input options to define river/stream networks in the basin: (1) a generated stream network based on DEM or (2) a user given real stream network. However, the DEM based network does not always represent the real stream network due to various constraints, for instance, generation of false rivers from coarser resolution DEM data. In this study, the actual stream networks were provided by the National Hydrography Datasets (2010) (figure 3.4).

3.4.3. Reservoirs and wetlands

The Otter Tail River watershed (figure 3.5) has many wetlands and reservoirs compared to other watersheds. If a subbasin has more than 5% of its area as open water then a wetland was considered in the model and the surface area of the wetland was optimized during model calibration. If a reservoir exists in the downstream of any rivers then the model was allowed to consider reservoir's effects on streamflows. As shown in figure 3.5, three reservoirs, namely, the Orwell Dam, White Rock Dam, and North Bay Dam, were modeled at the downstreams of Otter Tail River, Bois de Sioux River, and Western Wild Rice River, respectively. The observed outflow data from the Orwell Dam were collected from the database of US Army Corps of Engineers (2011).

3.4.4. Soil data

The STATSGO soil dataset was used for SWAT for the URRNB. The resolution of STATSGO soil data was 1:250,000. STATSGO classifies soil into four hydrologic soil groups (i.e., A, B, C, and D soils) on the basis of runoff potential of the soil where A has the lowest runoff potential due to high sand (above 90%) whereas D has the highest runoff potential with more than 40% clay. Moreover, D represents a high groundwater table with an impermeable soil horizon near to soil surface. It is evident that some of tiled areas are also seen in well drained soils (C or B) in URRNB where a high ground water table exists due to glacial aquifers (Schuh, 2008). Therefore, both D and C soils were considered as poorly drained soils in this study.

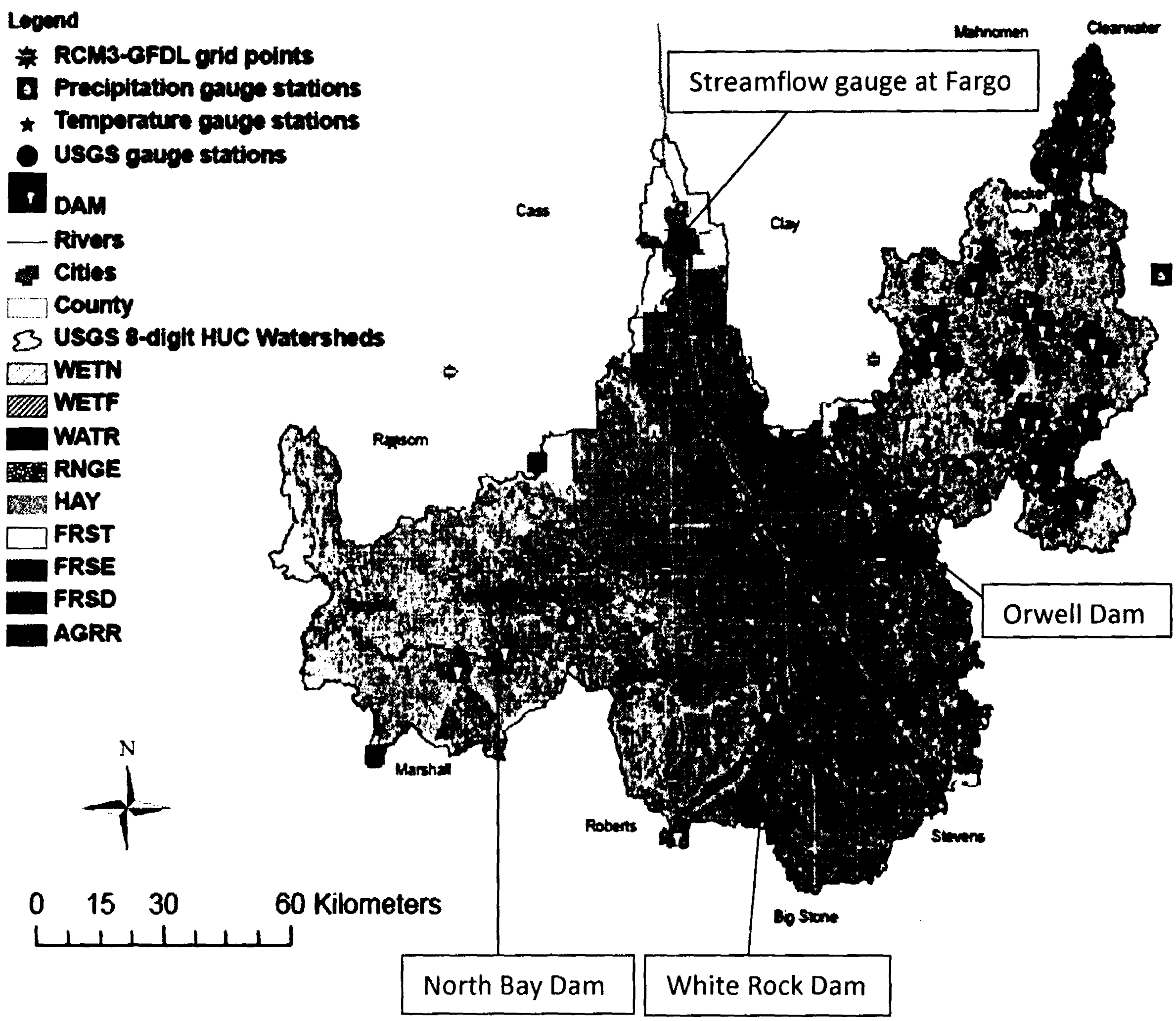


Figure 3.5. Location of different gauge stations and land use pattern within the URRNB (WETN-Wetland non-forested, WETF-Wetland forested, WATR-Open water body, RNGE-Range land, FRST-Mixed forest, FRSE-Evergreen forest, FRSD-Deciduous forest, and AGRR-Agricultural land).
Data sources: The National Hydrography Datasets, the North Dakota Geographic Information Systems database, the Multi-Resolution Land Characteristics Consortium database, the USGS water database, the National Oceanic and Atmospheric Administration's weather database and the North American Regional Climate Change Assessment Program database.

3.4.5. Land use/land cover data

The National Land Cover Dataset 2001 (NLCD 2001) developed by the Multi-Resolution Land Characteristic Consortium (MRLC) was used in this study for the purpose of HRU definition. The NLCD 2001 represents all cultivated crops under a single group coded as row crops whereas the land use database of National Agricultural Statistics Service (NASS) delineates all major crops separately. The row crops of the NLCD2001 dataset were divided into two major crop groups (i.e., corn and soybean) based on the NASS 2006 database. It can be mentioned that the NASS data prior to 2006 were not available for the entire basin.

3.4.6. Streamflow and tile flow data

The monthly observed streamflows for 22 years (from 1988 to 2009) were collected at the five U. S. Geological Survey (USGS) gauge stations (figure 3.5). These stations were: (1) USGS 05051300 at Bois de Sioux River near Doran, MN, draining Bois de Sioux and Mustinka watersheds, (2) USGS 05046000 at Otter Tail River near Fergus Falls, MN, draining Otter Tail River watershed, (3) USGS 05051500 at Red River of the North at Wahpeton, ND, draining above three watersheds, (4) USGS 05053000 at Western Wild Rice River near Abercrombie, ND, draining Wild Ricer River watershed, and (5) USGS 05054001 at Red River of the North at Fargo, ND, draining the entire URRNB. Two years (2008 – 2009) of daily tile flow data were collected from the 20 ha experimental field located in Fairmount, Richland County, ND (Pang et al., 2010). This field was under controlled subsurface drainage and subirrigation systems. The field has C soils.

3.4.7. Weather data

The weather data (precipitation and temperature) for 22 years (1988 – 2009) were collected from the database of Cooperative Observer Network (COOP) of National Oceanic and Atmospheric Administration (NOAA). For every delineated subbasin, SWAT uses the weather data from the nearest station. Thirteen weather stations within and near the basin's boundary were used for this study (figure 3.5). These stations, having less missing data and with uniformly distributed over the basin, were chosen so that the spatial variability of climate data would be minimized.

3.4.8. Projected future weather data

Though the goal of this study was not directly related to climate change, the future climate scenarios were taken into account when the impacts of projected tile drained areas on streamflows were analyzed. The climate estimates available for the period of 2040 – 2070 were collected from the database of the North American Regional Climate Change Assessment Program (NARCCAP) (2011). For convenience, the 2040-2070 climate data sets will, hereafter, be called as mid 21st century or simply 2050 climate . However, only the RCM3-GFDL climate model generated estimates were used, where RCM3 stands for the Regional Climate Model version-3 and GFDL (a General Circulation Model) stands for the Geophysical Fluid Dynamics Laboratory. RCM3-GFDL means that the future global climate estimates projected by the GFDL model were downscaled by the RCM3 regional model. As shown in figure 3.5, there were seven RCM3-GFDL grid points within or near the study area and the spatial resolution of these grids was 50 by 50 km. The raw precipitation data generated by the RCM3-GFDL model were at a 3 hrs interval and were converted to the daily values.

3.5. Watershed delineation and HRU definition

As shown in figure 3.6, the URRNB was delineated into 31 subbasins and 937 HRU's. While defining the HRU, the threshold values for land use/land cover, soil and slope were assigned as of 4, 10, and 15%, respectively. If the percentage of any class within each

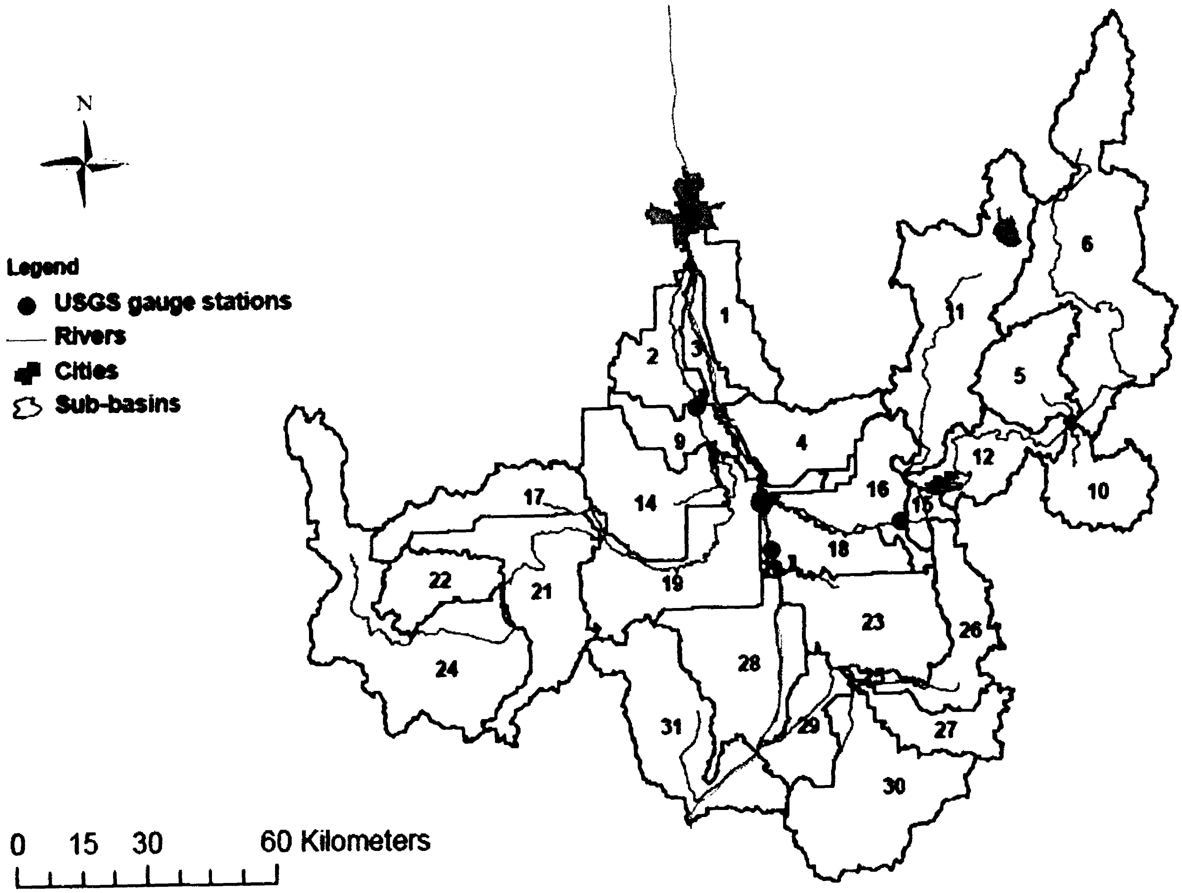


Figure 3.6. Delineated subbasins in the URRNB.
Data sources: The National Hydrography Datasets, the North Dakota Geographic Information Systems database and USGS water database.

variable (land use, soil orslope) is below the threshold value then that particular class will not be considered in modeling rather that class will be merged proportionally with remaining classes. For example, if in a HRU urban land use class is below 4% then the model will not consider this urban land use rather it will be proportionally merged among others having equal to or more than 4% of areal coverage.

3.6. Mapping tile drained areas

If only a portion of the basin area is under subsurface drainage then the information about the locations and areas of the tile drained subbasins needs to be provided to model tile flow in SWAT. In this study, a GIS based decision tree classification method (DTC; see also Sugg, 2007; Naz and Bowling, 2008) was applied to identify the approximate tile drained areas in the URRNB. The processes of mapping tiled area and selecting tiled HRUs are shown in figure 3.7. Firstly, soil (STATSGO) and land use/land cover (NLCD2001) data layers were overlaid to obtain the raster cells (10 m × 10 m), in which, row crops grow at the poorly drained soils. Since flat topography (slope ≤ 1%) that impedes quick surface runoff is another reason for tile drainage, land with less than or equal to 1% surface slope was overlaid with the previously created crop-soil raster data layer. The resultant layer was the potential tile drained (PTD) area for the URRNB. For C and D soils, the PTD area was mapped separately; and for simplicity, they are called C-PTD and D-PTD areas. The existing tiled area was determined based on D-PTD area only. The PTD area was laid with the delineated watershed map (figure 3.6) to identify the PTD sub-basins, the sub-basins that overlap with the PTD areas.

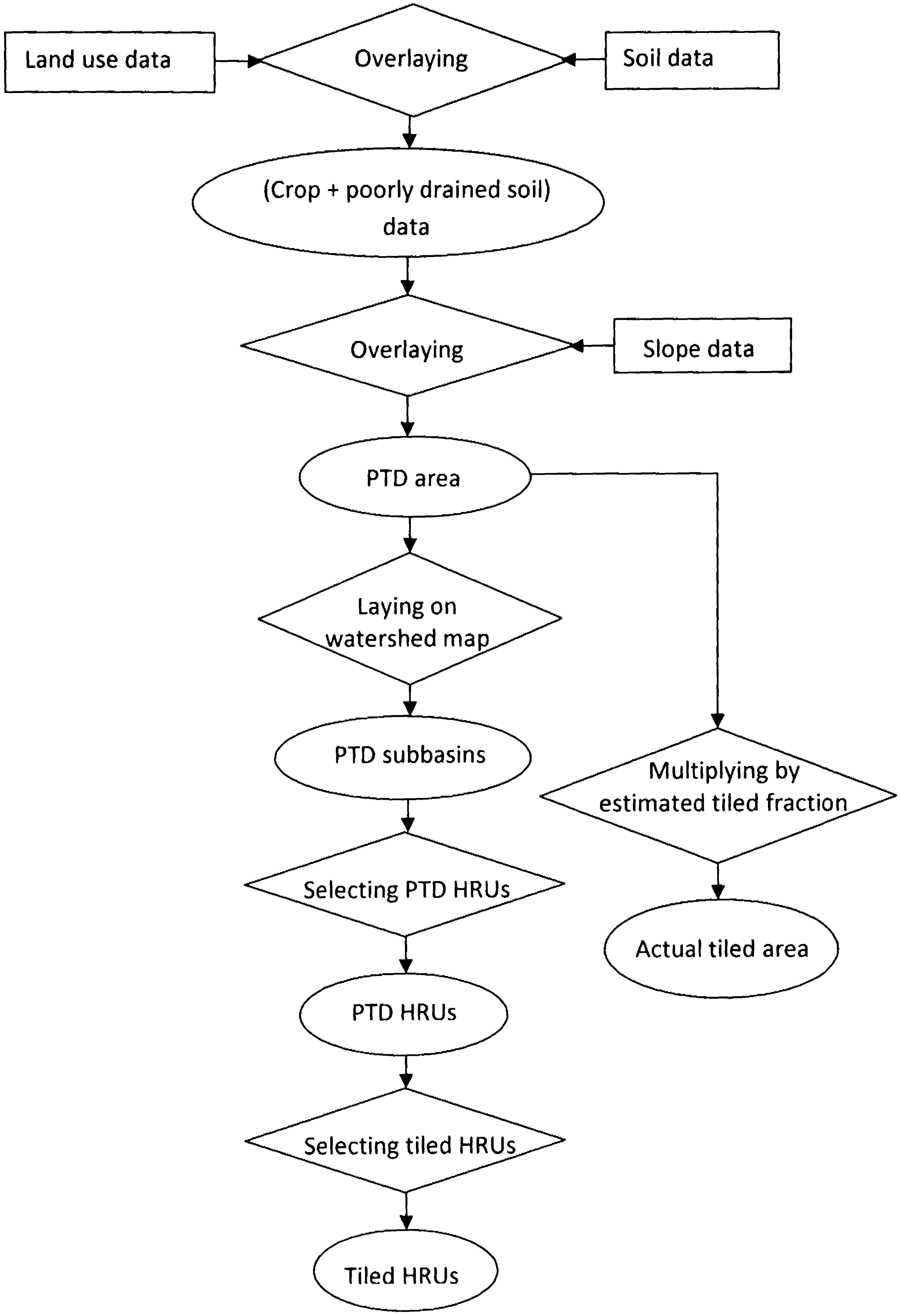


Figure 3.7. Flow diagram of tile drained area mapping and identifying tiled HRUs.

The percentages of the current tile drainage acreages in different counties estimated by Schuh (2008) for the North Dakota side and by Sugg (2007) for the Minnesota side were used to estimate the actual tile drainage areas in URRNB. The county based existing tile drained area reported by Schuh (2008) and Sugg (2007) were distributed proportionally among the PTD subbasins within each county. Since the exact spatial locations of these existing tile drained areas within a county were unknown, their locations were modeled within the boundary of the PTD areas mapped by the decision tree classification method.

Since SWAT computes water balance components at the HRU level, the model requires specifying which HRUs are tile drained. The HRUs with crop land use, soil D or C, and slope less than or equal to zero were identified from each PTD subbasin; and these HRUs were termed as PTD HRUs. Desired numbers of the tiled HRUs were selected from the PTD HRUs of each PTD sub-basin so that the total area encompassed by the HRU's equaled the estimated area of the existing tiled fields in that sub-basin.

3.7. Model calibration and validation

The two versions of SWAT with different tile drainage algorithms were first calibrated and validated against the daily tile flow dataset from Fairmount. The calibration and validation time periods were 2008 and 2009, respectively. The calibrated tile drainage parameters were then transferred to the SWAT model for the entire URRNB. The URRNB model was then calibrated and validated against the monthly stream discharges recorded at the five USGS stream stations. The calibration and validation periods are 1990-2000 and 2001-2009, respectively. The calibrated SWAT models were then used to analyze the impact of tile drainage on the water budget and streamflows in the URRNB under different scenarios.

3.8. Statistical indicators to evaluate model's performance

The model's performance was evaluated by the following indicators.

3.8.1. Nash-Sutcliffe efficiency (NSE)

The NSE (Nash and Sutcliffe, 1970) is the measure of how closely the simulated values match with the observed values. It is represented by

$$\mathrm{NSE} = 1 - \left[\frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}\right] \tag{3.14}$$

where O_i and S_i are the i^{th} observed and predicted streamflows, respectively; $\bar{O}$ is the average observed streamflows; and n is the number of observations. The NSE takes a value from -∞ to 1, with greater values indicating better agreement.

3.8.2. Coefficient of determination (R^2)

The R^2 represents the variation associated with the observed data to be explained by the model.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2} \times \sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2}}\right]^2 \tag{3.15}$$

where $\bar{S}$ is the average model-predicted streamflows and other symbols are defined as the same as in equations (3.14).

3.8.3. Percent of bias (PBIAS)

PBIAS stands for the percent of bias that indicates the average tendency of over prediction or under prediction by the model.

$$\text{PBIAS} = \left[\frac{\sum_{i=1}^{n} S_i - O_i}{\sum_{i=1}^{n} O_i}\right] \times 100 \tag{3.16}$$

3.9. Future tile drainage and climatic scenarios

It was postulated that the extent of tile drainage area would be increasing in the RRV to improve agricultural production. Two different tile drainage scenarios are combined with two different future climate conditions (with or without climate change) to create four different future scenarios (see Table 3.1) to simulate the impact of tile drainage on streamflows in the URRNB in the future. The two different tile drainage scenarios are the D soil PTD area (5.7% of the basin area); and the sum of the C soil PTD area and the D soil PTD area (17.4% of the basin area). The PTD areas were described in Section 3.6.

Table 3.1. Design of future scenarios.

Tiled drained area	Without climate change	With climate change
D soil PTD area (5.70% of basin)	Scenario - 1	Scenario - 3
(C+D) soil PTD area (17.40% of basin)	Scenario - 2	Scenario - 4

4. RESULTS AND DISCUSSION

4.1. Tile drained area estimation

Figure 4.1 shows the spatial extents of the C- PTD area (purple colored) and the D- PTD area (red colored) in the URRNB estimated using the DTC technique. As shown in the figure, the major portion of the D- PTD area was found along the Red River main stem covering about 940 km^2, which is about 5.7% of the entire basin area. The existing tile drained area in URRNB was estimated to be 125 km^2, equivalent to 0.75% of the total basin area. The estimated total area of the existing tiled fields was as same as those reported in Schuh (2008) and Sugg (2007). However, the tile drained areas estimated in this study were assumed to be overlaid with D soil, which does not necessarily reflect reality. Some existing tiled fields are overlaid with C soils. For example, the 20 ha experimental tiled field in Fairmount (Richland County, ND) was on C soils. The total (C + D) - PTD area was about 2876 km^2 (or 17.40% of the basin area). Srinivasan et al. (2010) found that it was satisfactory when SWAT was applied, in conjunction with the DTC method, to model the impact of subsurface drainage in the Upper Mississippi River Basin; whereas Sugg (2007) suggested that the estimation of tiled area by the DTC method was more reliable for heavily tiled area than for less tiled area.

4.2. Comparison of tile drainage algorithms

The SWAT model was first calibrated and validated against 2 years tile flow daily measurements collected at the Fairmount experiment site to compare the two tile drainage algorithms adopted in different versions of SWAT. The calibrated values of the parameters associated with the two tile drainage algorithms are provided in Table 4.1.

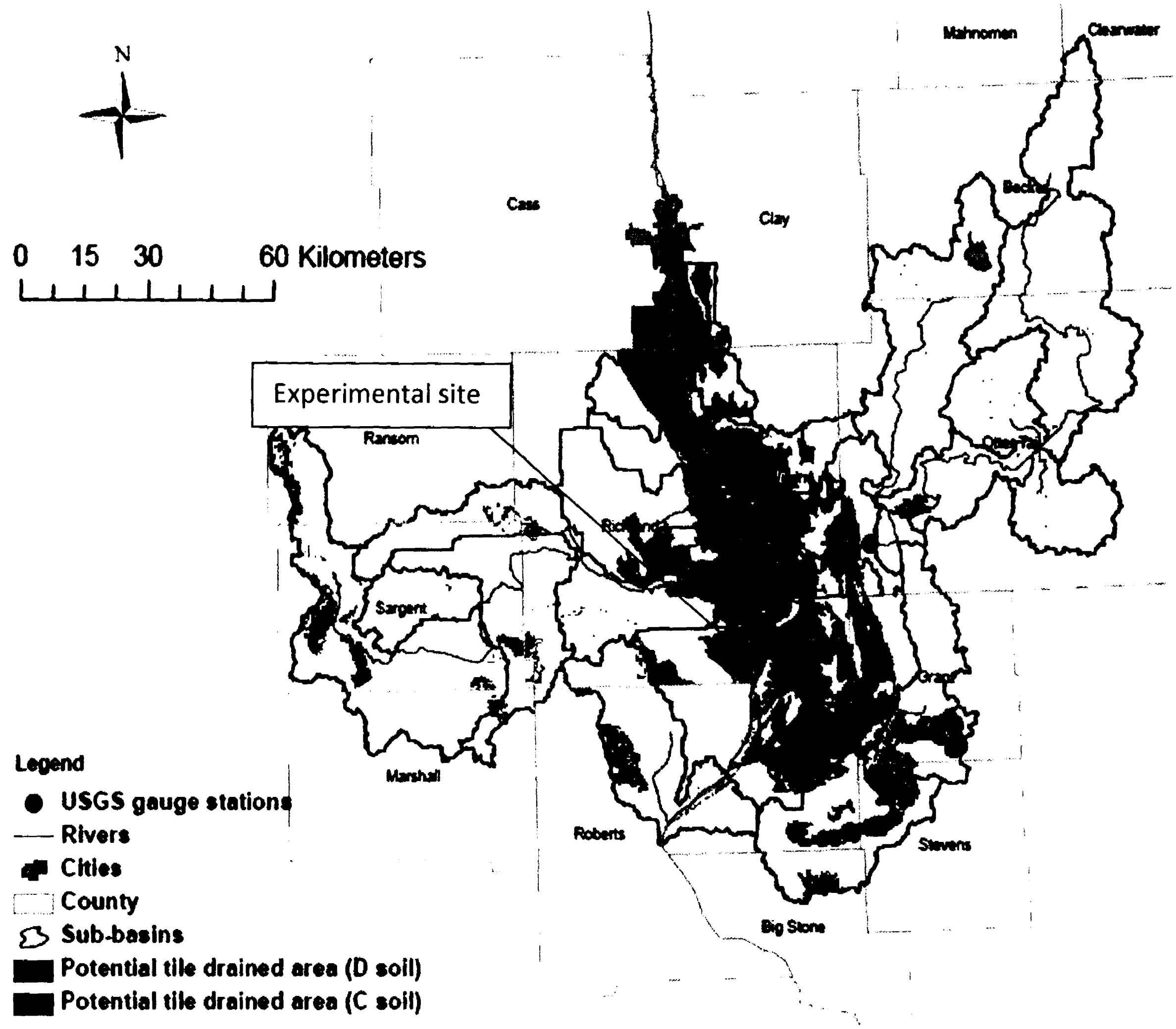
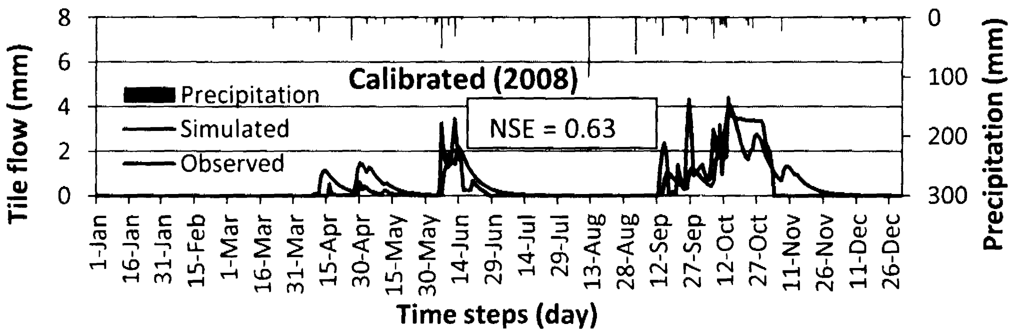


Figure 4.1. Potential tile drained areas in the URRNB estimated by the decision tree classification method.
Data source: As mentioned in figure 3.4.

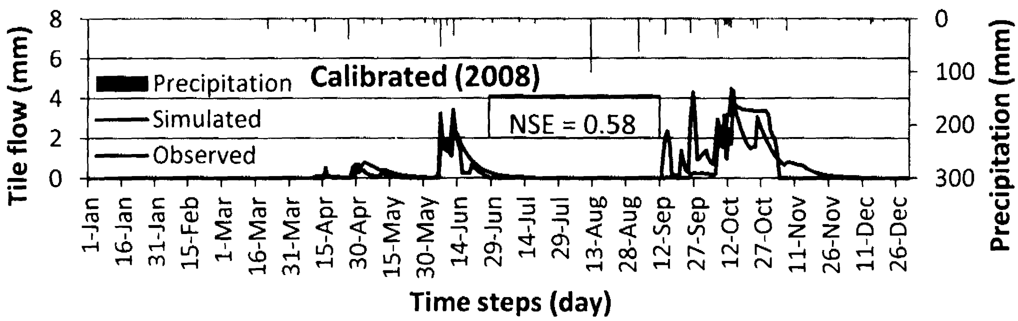
Table 4.1. Calibrated parameters of simple and Hooghoudt-Kirkham tile algorithms.

Parameters	Description	Simple algorithm	Hooghoudt-Kirkham algorithm
TDRAIN	Time to drain soil to FC (hrs)	48	–
GDRAIN	Drain tile lag time (hrs)	168	–
DEP_IMP	Depth to impervious layer in soil profile (mm)	1250	1250
RE	Radius of tile drains (mm)		30
DC	Drainage coefficient (mm)		13
LATKSATF	Conversion factor for saturated hydraulic conductivity		1.5

The comparisons of calibration (2008) and validation (2009) are shown in Figures 4.2 and 4.3, indicating a similar overall performance for both algorithms. The simple algorithm had slightly greater Nash-Sutcliffe coefficients than the Hooghoudt-Kirkham algorithm during both calibration and validation periods. It is also noticeable that Hooghoudt-Kirkham algorithm had a better performance than the simple algorithm during the late spring and early summer, while it had a worse performance than the latter during the early fall season. Both algorithms produced trace tile flow during the winter and the growing season when the tile flow was not actually observed. During the calibration time

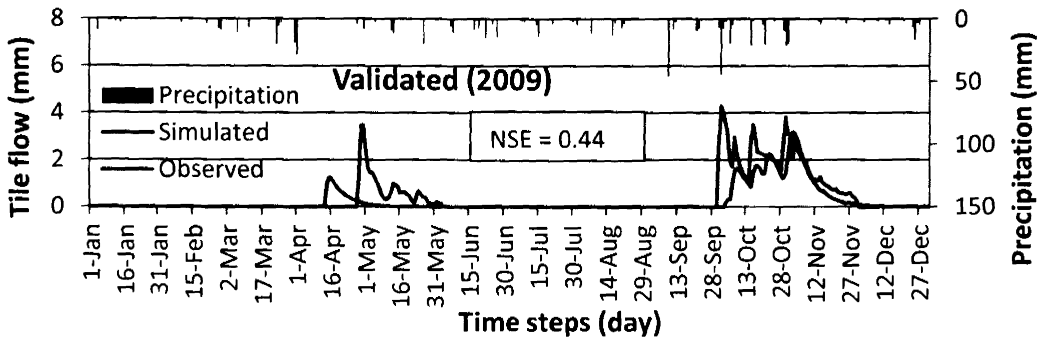


(a) Simple tile algorithm

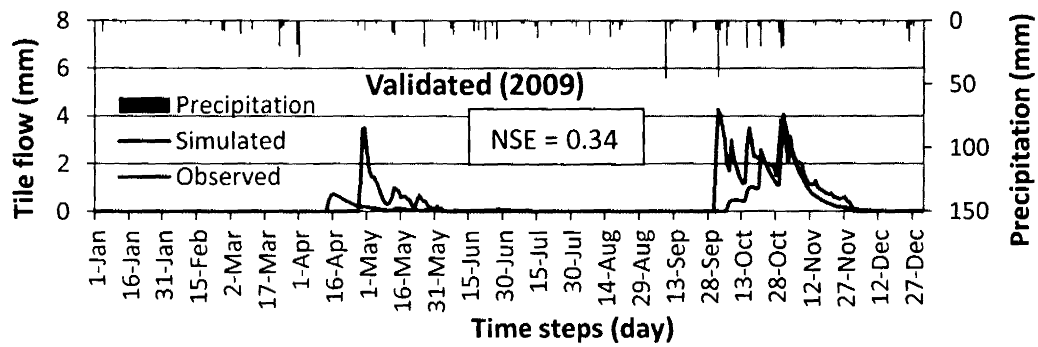


(b) Hooghoudt-Kirkham tile algorithm

Figure 4.2. Simulation performance of two tile algorithms during calibration (2008) (a) Simple and (b) Hooghoudt-Kirkham.



(a) Simple tile algorithm



(b) Hooghoudt-Kirkham tile algorithm

Figure 4.3. Simulation performance of two tile algorithms during validation (2009) (a) Simple and (b) Hooghoudt-Kirkham.

period the simulated tile flow time series ended about one month later than the observed (figure 4.2); while during the validation period, the tile flows simulated by both algorithms started about two weeks earlier than the observed flow (figure 4.3). This is because the field was under controlled subsurface drainage systems and the sump pump operation time was not simulated. For example, the simulated tile flow starting about two weeks earlier than the observed was because the land owners were asked by the local water board to turn off their sump pumps when the area was experiencing a historic flood in spring 2009.

Overall, both algorithms were able to simulate the pattern of the observed tile flow; and did well in the summer (June-August) and in mid-fall (October). However, both algorithms over-predicted the tile flow during late spring (April-May) and under-predicted during the early fall season (September). Four major possible reasons for the model's deficiency are suggested: First, there was lack of accurate weather inputs (precipitation and temperature). The nearest weather station was about 13.5 km away from the tiled field. Second, SWAT was limited in modeling soil temperature and soil water movement during spring snowmelt time. SWAT estimates soil temperature at different depths based on air temperature. The modeled average lag time between air and deeper soil temperatures was found to be 25-27 days. In a field study in the Red River basin, Jin et al. (2008) found that only the temperature of the upper 30 cm soil was influenced by air temperature and the lag time to reach the minimum temperature at the deeper soil was about 40 days. Similar results were also found in an experiment at Valdai, Russia (Luo et al., 2003). Furthermore, SWAT does not take into account the influence of snowpack thickness on the vertical soil temperature profile which may also affect infiltration processes during snowmelt (Luo et al., 2003, Iwata et al., 2010). Third, the underestimation in the beginning of fall (mid September – mid October) simulation might be due to higher soil water provided by subirrigation in mid July-August. Fourth, SWAT used an artificially created perched water table to generate lateral tile flow by assuming an impervious soil layer at 1250 mm, which did not reflect the reality of the glacial aquifer of RRNB. SSURGO database (NRCS web soil survey, www.websoilsurvey.nrcs.usda.gov) suggests that, for Doran soil in the Fairmount experiment site, the depth to impervious layer is about 2000 mm and the depth to groundwater table fluctuates from 457 to 1066 mm.

4.3. Model calibration and validation at the watershed scale

Given that both algorithms had a similar performance in simulating tile flow in the field scale and that the SWAT model with the simple algorithm ran faster during execution in computer than the SWAT model with Hooghoudt-Kirkham algorithm, the SWAT model with the simple algorithm was chosen to model the impact of tile drainage on streamflows in the URRNB at the watershed scale. The values of the parameters governing the tile drainage process were directly transferred into the watershed-scale SWAT model for the URRNB while the model parameters governing other hydrological processes (i.e., land hydrology and channel routing) were calibrated against the streamflow measurements at the five USGS stream stations at a monthly time step. The calibrated values and the ranges of the important SWAT model parameters are listed in Table 4.2.

In addition to curve number (CN2), the parameters associated with snowmelt algorithm mostly controlled the overall performance of the model. The basin level parameters of SMTMP, TIMP and SURLAG mostly controlled the model's performance in simulating the spring snowmelt driven streamflows (Wang and Melesse, 2005; Wang et al., 2008). The HRU level parameter ESCO took a value of unity (1.0), indicating that no evaporation was allowed from deep soils. Similarly, EPCO took a value of unity, indicating that plants were allowed to draw water from deep soils. These calibrated parameters (ESCO and EPCO) ensured sufficient water in the root zone so that crop experienced less water stress. In the Otter Tail River watershed, the most sensitive parameters were related to surface water and groundwater interaction. The relative lower values of AWC and GW_DELAY ensured sufficient and rapid shallow aquifer recharge, while the relative higher value for ALPHA_BF and GW_SPYLD allowed fast groundwater discharge.

Table 4.2. Calibrated parameters of SWAT model with their default values.

Parameters	Description	SWAT default values	Calibrated values
Basin level			
SFTMP	Snowfall temperature (^0C)	1.00	0.00
SMTMP	Snowmelt temperature (^0C)	0.50	1
TIMP	Snowpack temperature lag factor	0.2	1
SURLAG	Surface runoff lag time (day)	4	0.2
Otter Tail watershed			
AWC	Available water capacity (mm/mm)	0.11-0.20	0.01 - 0.08
GW_SPYLD	Specific yield of shallow aquifer (m^3/m^3)	0.003	0.3
ALPHA_BF	Baseflow factor (days)	0.048	0.5
GW_DELAY	Groundwater delay (days)	31	5
SHALLST	Initial depth of water in shallow aquifer (mm)	0.5	1000
HRU Level			
CN2	Curve number	42-90	30 -78
ESCO	Soil evaporation compensation factor	0.0	1.0
EPCO	Plant uptake compensation factor	0.0	1.0
TDRAIN	Time to drain soil to FC (hrs)		48
GDRAIN	Drain tile lag time (hrs)		168
DEP_IMP	Depth to impervious layer in soil profile (mm)		1250
Reservoirs			
RES_VOL	Initial volume (m^3)		300,0000 - 405,0000
RES_PVOL	Volume at principal spillway (m^3)		405,0000 - 700,0000

4.3.1. Model performance for long-term simulation

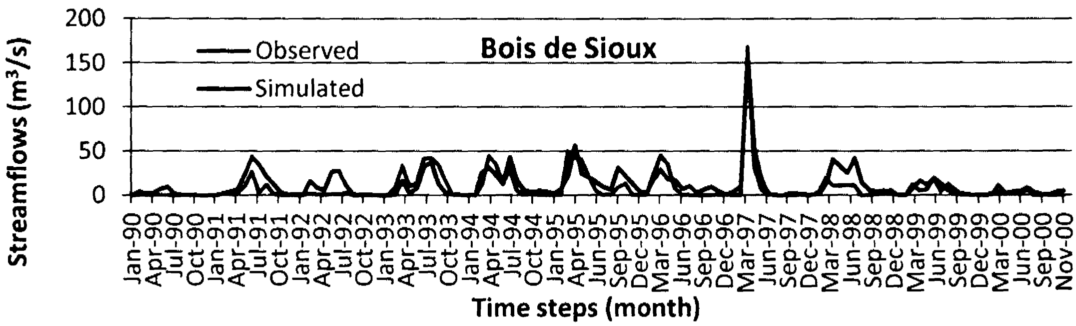
Table 4.3 lists the performance indicators of the SWAT model in simulating the streamflows at the five USGS gauge stations during the calibration (1990-2000) and validation (2001-2009) periods. The consistently high values for both NSE and R^2 at all five stations indicate that the SWAT model was able to simulate the monthly streamflows in URRNB reasonably well. The model showed the best performance for the Otter Tail River watershed and the worst performance for the Wild Rice River watershed. An average tendency of overestimation of streamflows was reflected by the positive PBIAS values, shown in almost all stations except for the Otter Tail River watershed, where a slight underestimation was observed.

Table 4.3. Performance of SWAT in streamflow simulation at five USGS stations.

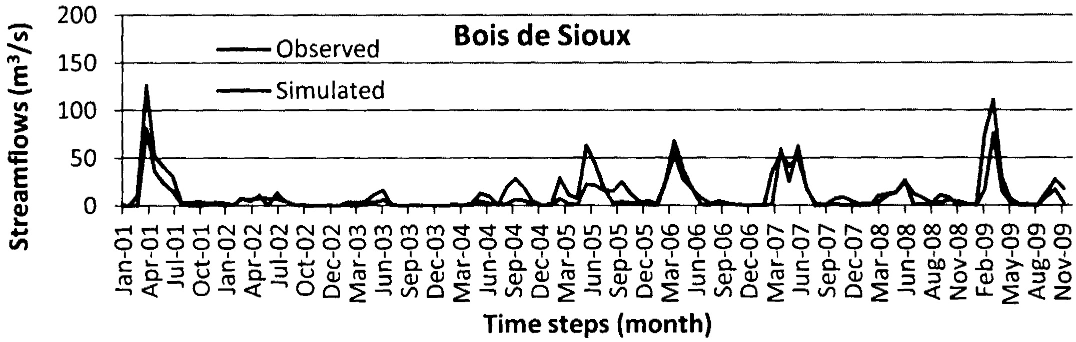
USGS streamflow gauge stations	Calibration			Validation		
	NSE	R^2	PBIAS (%)	NSE	R^2	PBIAS (%)
Bois de Sioux River at Doran	0.72	0.74	26	0.70	0.75	27
Red River at Wahpeton	0.83	0.84	11	0.86	0.86	6
Otter Tail River at Fergus Falls	0.99	0.99	-1	0.98	0.98	-2
Wild Rice River at Abercrombie	0.69	0.85	40	0.72	0.72	9
Red River at Fargo	0.84	0.93	8	0.87	0.89	2

Figures 4.4-4.8 shows the graphical comparisons of the model simulated and observed monthly average streamflows at the five USGS gauge stations. In the Bois de Sioux watershed, the model generally underestimated snowmelt driven spring streamflows with the worst performance in 2004 and 2005 (figure 4.4). But, the record high spring flood in 1997 was nearly perfectly simulated. The Lake Traverse created by the White Rock Dam (see figure 3.5) at the upstream of Bois de Sioux River may be partly a cause of the deficient model performance during 2004 and 2005. The errors associated with the calibrated parameters (e.g., volume, depth of water, hydraulic conductivity) of this lake might be the reason of model's poor performance as there was no observed

lake's outflow data. The streamflows of the Red River at Wahpeton were predominantly influenced by the Bois de Sioux River watershed, so the model performance at the Wahpeton station was similar to that the Bois de Sioux River (comparing figures 4.4 and 4.5).



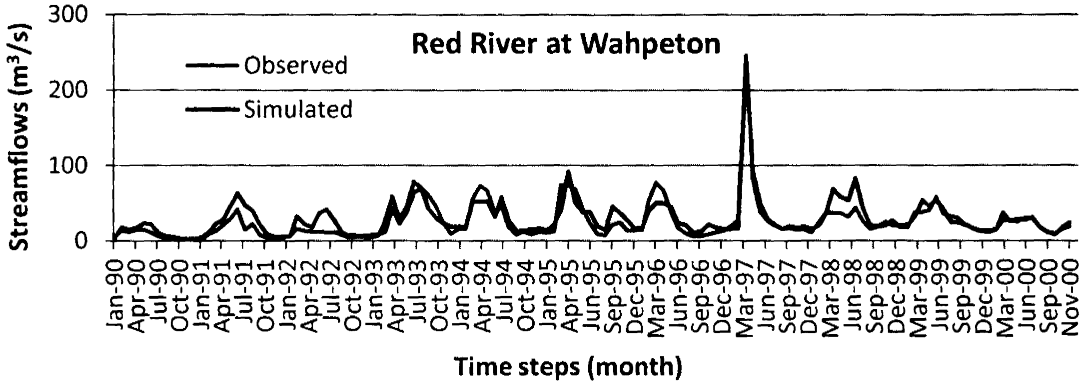
(a) Calibration



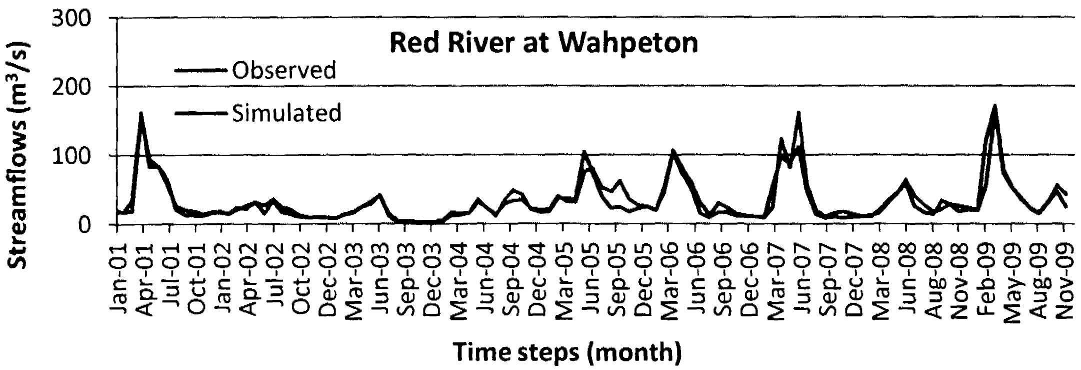
(b) Validation

Figure 4.4. Comparison of simulated and observed streamflows of the Bois de Sioux River at Doran (a) calibration and (b) validation.

The Otter Tail River is unique in the sense that it flows all year long and does not respond to extreme precipitation events as rapidly as other rivers in URRNB (see figure 4.6). This may be due to the extensive presence of scattered wetlands, reservoirs, lakes, and the shallow glacial aquifer in the Otter Tail River watershed, which had made the hydrological modeling of this watershed difficult (see Wang et al., 2008). When modeling the inflows to the Orwell Dam Reservoir using SWAT, Wang et al. (2008) was only able to achieve NSE values of 0.36 and 0.15 for model calibration (1969-1972) and validation (1972-1974), respectively. In this study, the model's performance was dramatically improved by allowing for surface water and groundwater interactions, which indicated that the glacial shallow aquifer played an important role in regulating the streamflows in the Otter Tail River.

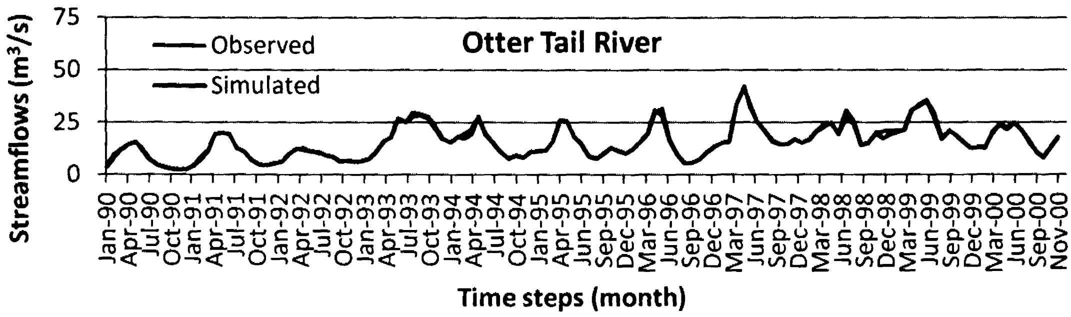


(a) Calibration

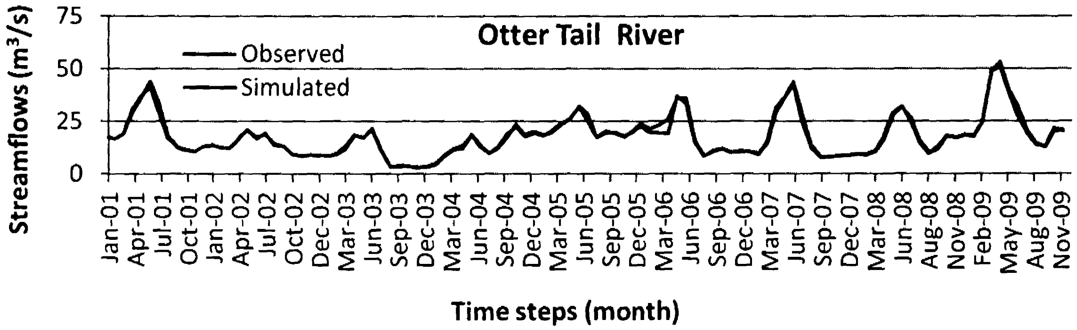


(b) Validation

Figure 4.5. Comparison of simulated and observed streamflows of the Red River at Wahpeton during (a) calibration and (b) validation.



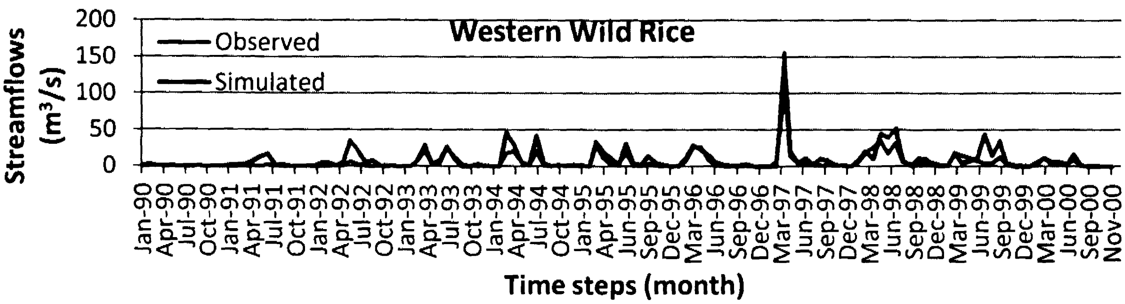
(a) Calibration



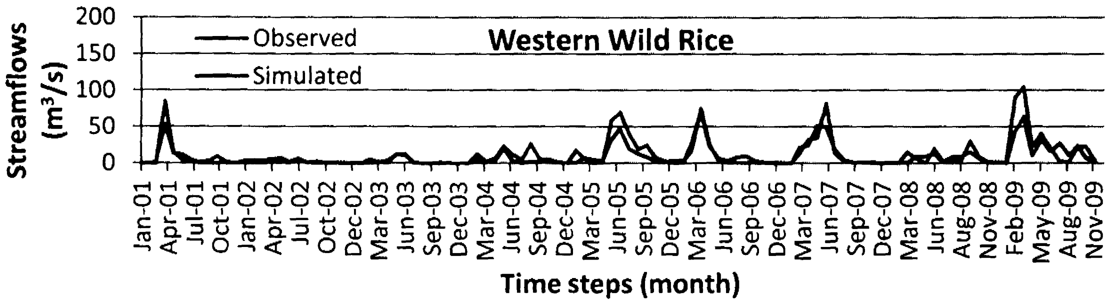
(b) Validation

Figure 4.6. Comparison of simulated and observed streamflows of the Otter Tail River at Fergus Falls during (a) calibration and (b) validation.

Figures 4.7-4.8 compared the model simulated and observed streamflows in Western Wild Rice River at Abercrombie and in Red River at Fargo, respectively. The model performance was generally satisfactory except that the model underpredicted the highest snowmelt driven spring flood peaks in 1997, 2001, and 2009. It should be noted that inclusion of Lake Tewaukon in the Western Rice River, created by the North Bay Dam, greatly improved the model performance.

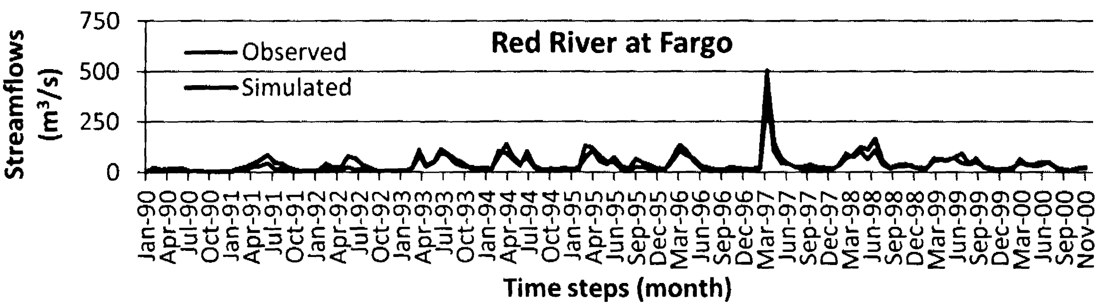


(a) Calibration

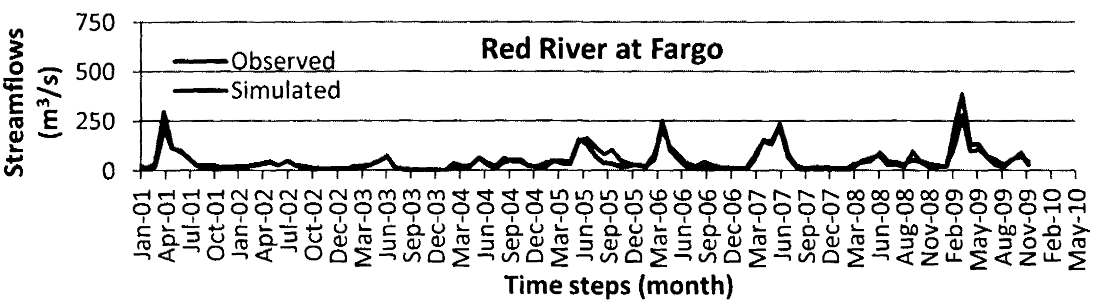


(b) Validation

Figure 4.7. Comparison of simulated and observed streamflows of the Western Wild Rice River at Abercrombie during (a) calibration and (b) validation.



(a) Calibration



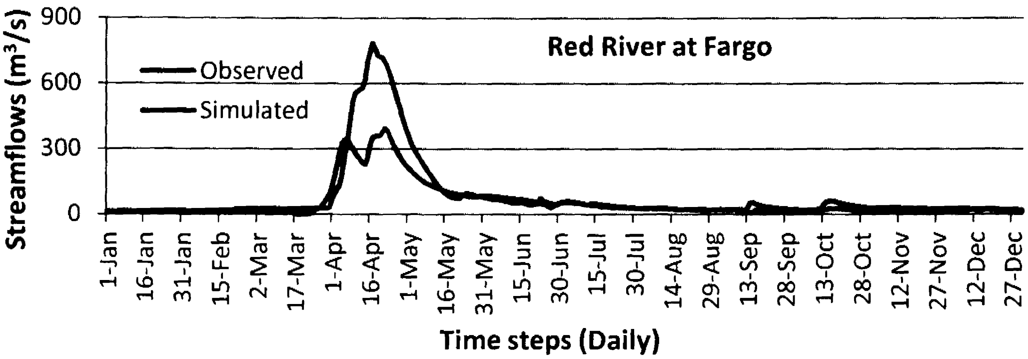
(b) Validation

Figure 4.8. Comparison of simulated and observed streamflows of the Red River at Fargo (Outlet of URRNB) during (a) calibration and (b) validation.

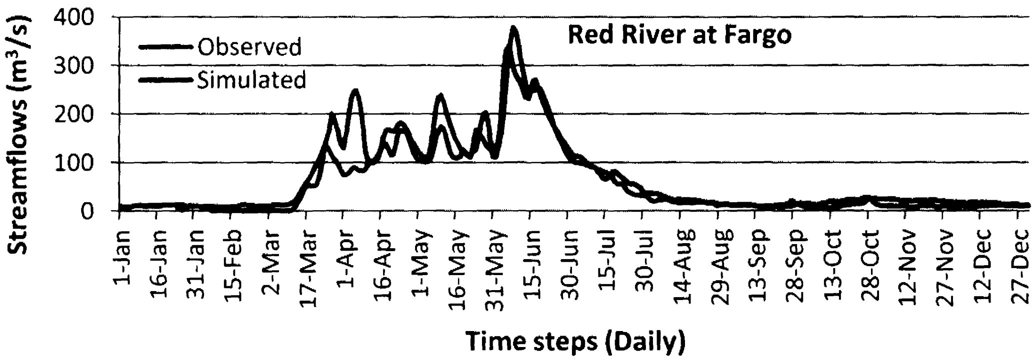
4.3.2 Model performance for spring flood simulation

To understand the underperformance of SWAT in simulating the highest spring flood peak flows, the calibrated SWAT model was run at a daily time step to simulate the streamflows in Red River at Fargo for three individual years (1997, 2007, and 2009) with severe flood records (figure 4.9). The model was able to simulate the 2007 spring flood reasonably well, but not for spring floods in 1997 and 2009, which were among the all-time highest records. A couple of reasons were suggested to explain the model's poor performance in modeling the spring flood peak flows. First, SWAT was not able to simulate the intermittent snowmelt process (Wang and Melesse, 2005). In late winter, daily air temperature was fluctuating around the freezing point. For example, air temperature may rise above 0 ^{o}C around noon, resulting snowmelt; then the air temperature may fall below 0 ^{o}C at night, causing the snowmelt water to freeze before reaching streams. The SWAT model was not able to simulate this intermittent snowmelt process resulting over-prediction during late winter and under-prediction during early spring (see figure 4.9(a)).

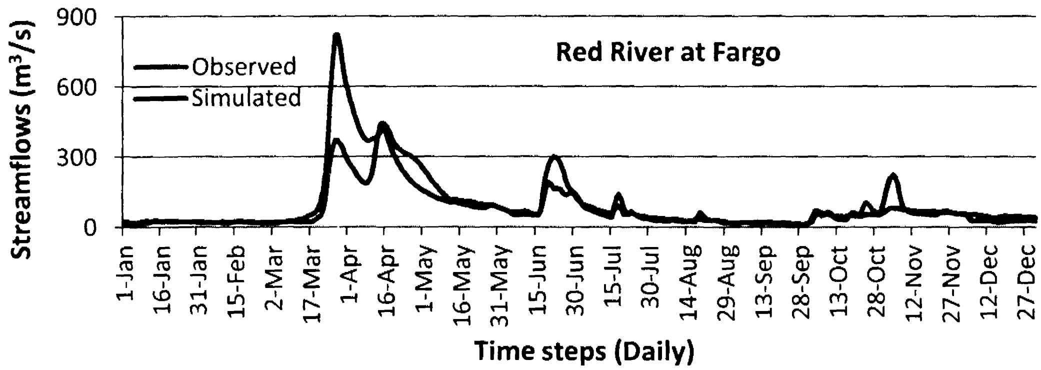
Another possible reason is that SWAT overestimates snowpack sublimation. When the snowmelt temperature factor (SMTMP) was increased from 0 to 1.5 ^{o}C to intensify the snowmelt process in a relatively short time period snowpack sublimation, rather than the desired snowmelt water, increased by about 7%. If SWAT had the provision to control sublimation it may be possible to improve the model's snowmelt hydrology. It should be mentioned that the estimated ET, which accounted for about 69% of the average annual precipitation, was comparable to another SWAT modeling study in Minnesota (David Mulla, 2011, personal communication).



(a) Daily streamflows (1997)



(b) Daily streamflows (2007)



(c) Daily streamflows (2009)

Figure 4.9. Comparison of simulated and observed daily streamflows of the Red River at Fargo (Outlet of URRNB) (a) 1997, (b) 2007, and (c) 2009.

4.4. Impacts of tile drainage on water balance and streamflows

The calibrated SWAT model for the Fairmount experimental site was run with and without tiles to analyze the impact of tile drainage on water balance at the field scale whereas the calibrated SWAT model for the upper Red River of the North basin was run with and without tiles to analyze the impact of tile drainages on the water balance at the watershed scale and the streamflows of the RR at Fargo.

4.4.1. Impacts of tile drainage on water balance at field scale

The Fairmount experimental field was considered a prototype on evaluating how tile drainage can impact the other water balance components of hydrology. This field was fully under tile drained condition. Precipitation is the principal driving force of other hydrologic components at this site and its variation may produce different results of tile drainage's impact on other water balance components. The model was tested using two years of precipitation data - a higher than normal annual precipitation (793.8 mm) in 2008 followed by a lower than normal annual precipitation (646.4 mm) in 2009.

Tables 4.4 and 4.5 respectively showed the simulated annual water balance components with and without tiles in 2008 and 2009. In 2008, the tiled field produced 147mm (H_2O) in tile flow, which was equivalent to 19% of the annual precipitation and 40% of the annual water yield. In 2009, the tile field produced 84 mm (H_2O) in tile flow, which was about 13% of the annual precipitation and 30% of the annual water yield. From a 5 year field scale study conducted in the same region Sands et al. (2008) found that about 17% of annual precipitation was converted to subsurface drainage. Kladivko et al. (2004)

showed that 8- 26% of the annual precipitation could be converted into subsurface drainage based on a field study in Indiana.

Table 4.4. Changes in annual water balance components due to tile drainage in experimental plot (2008).

Water balance components	Without tile (mm)	With tile (mm)	Changes (mm)	Relative changes (%)
Precipitation	793.8			
Tile flow	—	147.1	—	—
Surface runoff	330.7	217.3	-113.3	-34.3
Lateral flow	0.5	0.2	-0.4	-71.2
Water yield	**331.2**	**364.5**	**33.3**	**10.1**
Groundwater recharge	0.00	0.00	0.00	0.00
Transmission loss	0.01	0.01	0.00	0.00
Evapotranspiration	399.9	399.2	-0.7	-0.2
Soil Water content	277.7	225.4	-52.3	-18.8

Table 4.5. Changes in annual water balance components due to tile drainage in experimental plot (2009).

Water balance components	Without tile (mm)	With tile (mm)	Changes (mm)	Relative changes (%)
Precipitation	646.4			
Tile flow	—	84.0	—	—
Surface runoff	290.6	192.5	-98.1	-33.8
Lateral flow	0.8	0.15	-0.6	-81.4
Water yield	**291.4**	**276.6**	**-14.7**	**-5.1**
Groundwater recharge	0.00	0.00	0.00	0.00
Transmission loss	0.01	0.01	0.00	0.00
Evapotranspiration	356.2	372.0	15.8	4.4
Soil Water content	280.3	227.0	-53.3	-19.0

In both years surface runoff and soil water contents were significantly affected by tile drainage, whereas groundwater recharge and transmission loss were unaffected. Since an impervious soil layer at the depth of 1250 mm was created in the model, deep percolation to the deep groundwater aquifer was not allowed. Therefore, groundwater recharge was not simulated in the tiled field. Lateral flow appeared to be greatly impacted by tile drainage in terms of relative changes (-71% in 2008 and -81% in 2009). But, the absolute changes were small, decreasing by 0.4 mm in 2008 and 0.6 mm in 2009 after the field was tiled.

It is interesting to see that, in both years, annual surface runoff decreased by about 34% and soil water content measured at the end of the simulation time decreased by about 19%. It was, however, a different story for evapotranspiration and water yield. Evapotranspiration decreased about 0.2% 2008 (wetter year), while it increased about 4.4% in 2009 (drier year). The pattern for water yield was just the opposite. Water yield increased by about 10% in 2008 and decreased by about 5% in 2009.

Although it is yet to be corroborated by further studies, it appeared that tile drainage might have made the wet year wetter and the dry year drier in terms of water yield from a 100% tiled field. Figure 4.10 compared the impact of tile drainage on water yield at a monthly basis in 2008 and 2009. Water yield during winter months (December – February) was negligible. Both years saw a decrease in water yield in early spring (March) and during the growing season (July-September) and an increase in late spring (April) and fall (October and November) due to tiles. The decrease of water yield due to tiles in March may be because the snowmelt water was able to infiltrate into the unsaturated soils drained by the tiles in the previous fall, referring to the increased water yield in October and November. The decrease of water yield due to tiles in the growing season was caused by lowest soil water content, which, in turn, was caused by highest ET. Though the total ET in growing season was not affected by tile drainage, the decreased soil water content even less than field capacity created extra buffer room in soil profile to hold more infiltrated water and resulted less water yield. In tiled field crop faced less water stressed (0.4 and 1.8 in 2008 and 2009, respectively) condition compared to un-tiled field which indicated a better crop growth indeed. The difference between the two years is that the water yield in May and June of 2008 increased after tiling, while that of 2009 decreased after tiling.

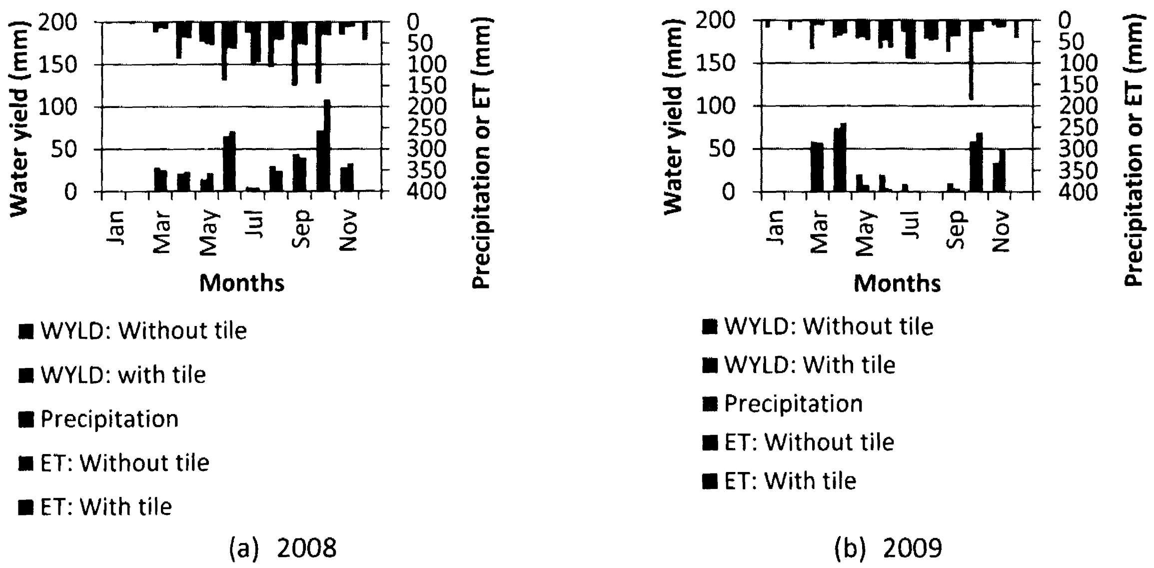


Figure 4.10. Impacts of tile drainage on monthly water yield in 2008 and 2009 (WYLD- Water yield and ET- Evapotranspiration).

4.4.2. Impacts of tile drainage on streamflows in Red River at Fargo

As discussed earlier, the SWAT model was less reliable when simulating the highest spring flood peak flows in the Red River. Therefore, our analysis of impact of tile drainage on streamflows was based on monthly average streamflows over a 10-yr simulation time period (2000-2009). Figure 4.11 displays the monthly average streamflows in the Red River at Fargo for zero tiling (0%) and the three different tiling rates in the basin – 0.75%, 5.70%, and 17.4%. The tiling rate of 0.75% refers to the percentage of the current tiled areas; 5.7% tiling rate means that the projected future tiled areas will be mostly limited within the coverage of D soils; and 17.4% means that the projected future tiled areas will be limited within the coverage of both C and D soils.

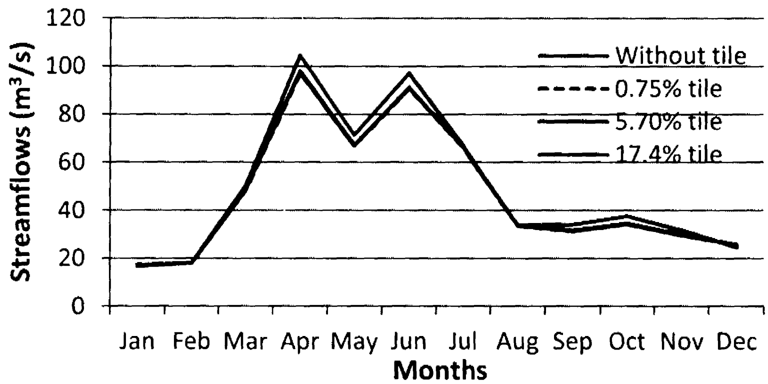


Figure 4.11. Impacts of tile drainage on 10 years (2000-2009) average monthly streamflows in Red River at Fargo.

Figure 4.12 shows the percentages of the changes in streamflow for the three different tiling rates versus zero tiling. As shown in figure 4.12, 0.75 and 5.70% tiling rates would not have significant effects on the monthly average streamflows in Red River at Fargo and the effect of the 17.4% tiling rate would be small as well. For a 17.40% tiling rate the streamflow might increase up to 1% in April and about 2% in fall (September to November). On the other hand, streamflow would decrease in the remaining months of the year.

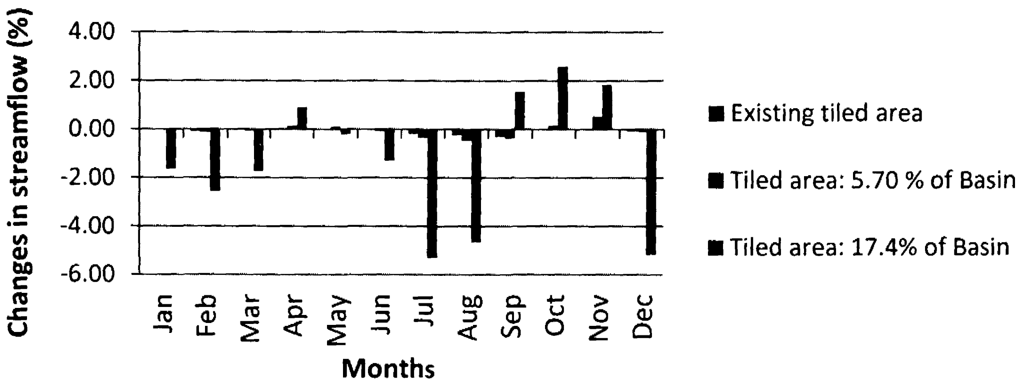


Figure 4.12. Changes in 10 years (2000-2009) average monthly streamflows in Red River at Fargo due to tile drainage.

4.5. Impact of tile drainage under future climate

4.5.1. Projected future precipitation and temperature

The five-year moving average of annual precipitation in URRNB increased about 14% in the past 15 years (from 1990 to 2005). RCM3-GFDL projected the average annual precipitation of the study area to increase from the current 600 mm to 920 mm in mid-21^{st} century, i.e., about 53 % of increase. However, these predicted increases in precipitation seemed elevated. For example, when assessing the future scenarios of climate change in the Upper Mississippi River Basin, Jha et al. (2006) assumed a maximum 20% increase in precipitation based on the average projected values from six general circulation models (i.e., CISRO-RegCM2, CCC, CCSR, CISRO-Mk2, GFDL, and HadCM3).

Since the goal of this research was not about climate change, we simply used RCM3-GFDL's projection as a reference of the future climate data to study the combined impact of tile drainage and climate change on streamflows in the Red River. As shown in figure 4.13, the monthly average precipitation increased in 2050 except for the month of

October. The monthly average precipitation of the present climate were calculated based on the recorded precipitation at thirteen weather stations within the URRNB for the past 10 years (2000-2009), while those of 2050 were calculated based on the RCM3-GFDL projection for the 30-year time slice of 2040-2070. Figure 4.14 also shows the standard deviation of the monthly average precipitation in the 2050 for the study region. The variations during summer months were about 40% while those during the winter months were about 55%.

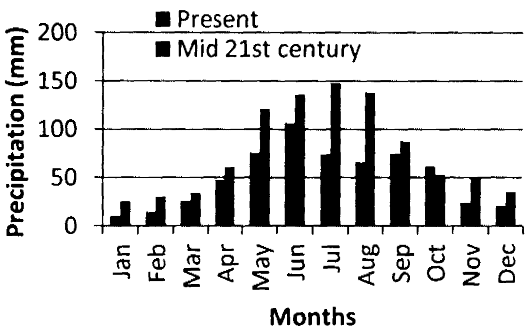


Figure 4.13. Comparison of monthly average precipitation between baseline period and mid 21st century.

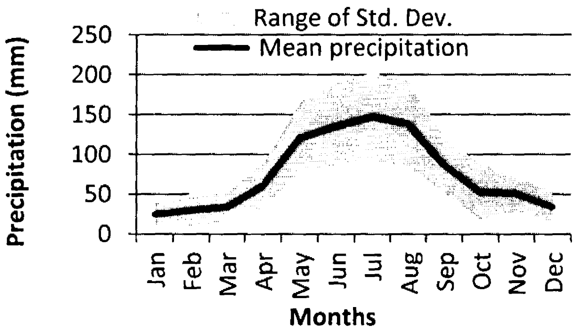


Figure 4.14. Variation of precipitation within a month in mid 21st century.

Figure 4.15 shows the comparison of monthly average temperatures between the present and 2050; and figure 4.16 shows their relative changes. The monthly average temperatures of the present and 2050 were calculated in the same way of calculating the monthly average precipitation. The monthly average temperature increased in March, May, and November while that in other months decreased except for April when monthly temperature remained the same.

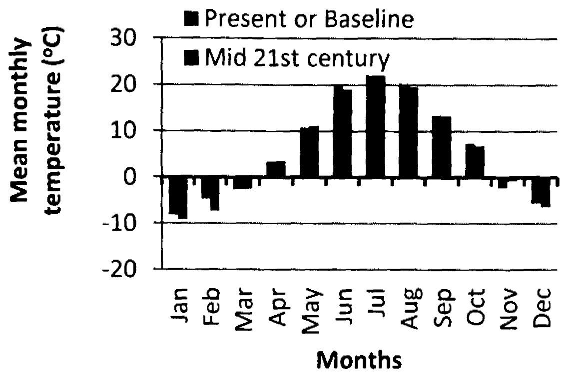


Figure 4.15. Comparison of monthly average temperature between baseline period and mid 21st century.

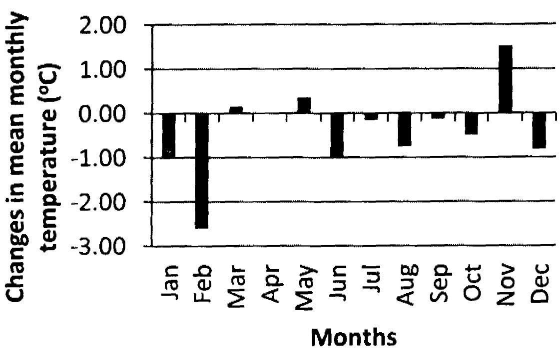


Figure 4.16. Changes in monthly average temperature by mid 21st century w. r. to corresponding baseline period's value.

4.5.2. Impacts of tile drainage under future climate

The possible changes in water balance impacted by tile drainage under future climate scenarios are shown in Table 4.6. These changes were estimated with respect to present climate scenario. The RCM3-GFDL climate model estimated that the annual average precipitation would increase by about 285 mm (47.54%) with respect to the present 10-yr average (2000-2009). Although the 17.40% tiling rate generated more tile flow when compared to 5.70% tiling rate, the former produced lower water yield than the latter. It is also interesting to show that the increase in ET for 17.4% tiling was actually lower than that for 5.7% tiling rate.

Table 4.6. Impacts of climate change on average annual water balance components for different tiling scenarios.

Water balance components	5.7% tiling Increase in mm (%)	17.4% tiling Increase in mm (%)
Precipitation	285 (47.54)	285 (47.54)
Tile flow	1.48 (243)	6.57 (94)
Surface runoff	177 (189)	170 (178)
Evapotranspiration	21.73 (5.32)	3.92 (0.96)
Water yield	198.22 (166)	188 (153)

5. CONCLUSIONS

5.1. Conclusions

A SWAT model was set up to analyze the impact of tile drainage on water balance and streamflows in the upper Red River of the North basin (16,500 km^2). The model was calibrated at both field and watershed scales. At the field scale, the model was calibrated and validated with two years of daily tile flow data collected at the Fairmount experimental site in Richland County, ND. The Nash-Sutcliffe efficiencies (NSE) for the field scale calibration and validation were 0.34-0.63. At the watershed scale, the model was calibrated and validated against 20 years monthly average streamflows recorded at five USGS gauge stations. The values of NSE for model calibration and validation ranged from 0.69 to 0.99, indicating that the SWAT model was reliable in predicting the monthly average streamflows in URRNB. But, the SWAT model's performance in predicting the highest spring flood peak flows was less satisfactory.

One of the challenges faced was to select an appropriate tile drainage algorithm to model tile flows in the watershed scale. In this modeling exercise two algorithms were compared: (1) the simple empirical algorithm, and (2) the Hooghoudt-Kirkham algorithms that were adopted in two different versions of SWAT. Although the Hooghoudt-Kirkham algorithms were physically-based and required comprehensive data about the field physical properties for parameterization, it did not perform as well as the simple algorithm did.

Another challenge was to identify the locations and to estimate the areas of the existing tile drained areas and the potential tile drained areas in the Red River Valley. The

GIS-based decision tree classification (DTC) method was used for such a purpose. The basic assumption of the DTC method is that soils that have the potential to be tiled are flat and poorly drained. Less than one percent (0.75%) of the basin area was estimated to be currently tiled and these currently tiled areas were mainly located in the Red River floodplain with poorly drained D soils. It was also estimated that up to 17.4% basin areas could be tiled in the future if assuming the potential tiled area to be on the NRCS classified C and D soils.

When modeling the 20 ha tiled field near Fairmount using 2008 (wetter year) and 2009 (drier year) data, the impacts of tile drainage on the water balance at the field scale results include:

1. Thirteen to nineteen percent (13-19%) of annual precipitation (or 30-40% of water yield) was produced as tile flow, which was consistent with the findings of Sands et al. (2008) who found that about 17% of annual precipitation was converted to subsurface drainage during a 5 years field scale study conducted in the same region.
2. Annual surface runoff decreased by about 34% and soil water content measured at the end of simulation time decreased by about 19% during both years.
3. Evapotranspiration decreased about 0.2% in 2008 and increased about 4.4% in 2009; while water yield increased by about 10% in 2008 and decreased by about 5% in 2009.

4. Monthly analysis showed that water yield decreased in March and during July-September (growing season); and increased in April and during October-November.

At the watershed scale the modeling results showed that a tiling rate of 0.75-5.70% would not have significant effects on the monthly average streamflows in Red River at Fargo. For the 17.40% tiling rate, the streamflow in Red River at Fargo might increase up to 1% in April and about 2% in fall (September to November), while decreasing up to 5% in the remaining months.

5.2. Suggestions for future research

1. The current SWAT model needs to be further studied in snow hydrology, particularly on the process of sublimation from snowpack and distribution of soil temperature in frozen soils.
2. Using remote sensing techniques and groundwater table information may give more realistic results in tiled area mapping.
3. A comparative study between SSURGO and STATSGO soil data is highly desirable to see their performance in simulating tile drainage flow by SWAT.
4. Accurate river geometry is very essential for river hydraulics. It seemed SWAT's DEM based river geometry was sometimes unrealistic. So, incorporation of HEC-RAS with SWAT may improve river flow modeling.

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