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Modeling Runoff from Small Agricultural Watersheds in Eastern South Dakota

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MODELING RUNOFF FROM SMALL AGRICULTURAL WATERSHEDS IN EASTERN SOUTH DAKOTA

BY

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This thesis is approved as a creditable and independent investigation by a candidate for the Master of Science degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this thesis does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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ABSTRACT

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The capability to be able to consistently and accurately model any problem has potential time and money savings. The present study aimed to determine if the Natural Resources Conservation Service's Curve Number (CN) model or the more detailed Soil and Water Assessment Tool (SWAT) Model can consistently and accurately model runoff events from small agricultural fields in Eastern South Dakota. The overall goal was to better understand models used to predict runoff and determine if they can produce accurate estimates of runoff from the watersheds being studied.

Runoff measurements were collected from an agricultural field located south of Coleman, South Dakota. The field of study was under a conventional tillage, two-year corn-soybean rotation. Three distinct watersheds make up the farm field with one flume at the lowest point for each watershed. Four years of collected rain data at the site (2013-2016) along with two years of runoff data (2015-2016) were used for modeling and subsequent statistical comparison. This study examined the collected runoff totals for rain events and evaluated the accuracy and precision of model predictions to the observed runoff totals.

For the two years studied, almost all predicted runoff events using the CN method were higher than the measured runoff totals. On average, the CN model over-predicted runoff totals by 300%. Adjustments to three areas of the CN model (initial abstraction

ratio, curve number, and watershed size) improved comparison statistics. However, none of the changes made to the CN model produced satisfactory statistical results.

The 2015 and 2016 runoff events were then compared to the SWAT model predictions. The first model run was with SWAT's recommended settings and produced higher runoff than was observed. Adjustments to three areas of the SWAT model (curve number (CN2), potential evapotranspiration method (IPET), and daily curve number calculation method (ICN)) were combined to improve comparison statistics. The SWAT model using Penman-Monteith method + Potential Evapotranspiration method + 10% decrease in CN2 produced the closest approximation to measured values relative to all models, including the CN model. This variation of the SWAT model did not produce a consistent and accurate model for all three watersheds, but it did produce partially acceptable results for the largest watershed.

Neither the CN nor SWAT produced a model that was statistically acceptable at predicting runoff for the studied agricultural watersheds. For further research it was decided to focus on changes to the SWAT model. Given this, the next steps would be: produce fewer outlets during the startup of the SWAT model, test the three watersheds as one large watershed in SWAT, and/or take soil samples at the testing site to determine if the soil is more hydrophilic than modeled.

CHAPTER 1

INTRODUTION

Runoff and its related problems are a known issue that affect watersheds of all sizes. From local issues, like roads washing out in the spring, to national issues such as the hypoxic problem down in the Gulf of Mexico, water runoff is a problem that affects most people sooner or later. The volume of runoff is not the main culprit. Moreover, what is being carried in the water creates problems, which is the case for the Gulf. According to the United States Environmental Protection Agency (EPA), nonpoint source pollution is the leading source of water quality impacts on surveyed rivers and lakes, with the largest contributor bring agriculture lands (Nasab, Singh, & Chu, 2017). The EPA and U.S. Geological Survey (USGS) combined spend millions of dollars a year to study and follow runoff and its effects on rivers and lakes (Swanson, 2013).

Runoff from South Dakota farm fields can make its way to streams and creeks, to the upper Mississippi and Missouri river basins, which flow down to the Gulf and contribute to the Gulf of Mexico hypoxic zone. This hypoxic zone is largely caused by excess nitrogen carried down to the Gulf via the Mississippi River. Agricultural and urban runoff are the largest contributors to nonpoint source pollution for United States waterways (Rabotyagov et al., 2010). South Dakota might not be the largest contributor to the problem but runoff from South Dakota does add to the problem. It is the shared responsibility of all states involved to improve procedures and refine nutrient applications to help solve problems created by over application and untimely application of nutrients.

Programming efforts like Wisconsin's Runoff Risk Advisory Forecast tool or the Fertilizer Forecaster tool from Pennsylvania help farmers best manage their application timing to minimize possible nutrient loss via runoff (USDA-ARS; Penn State Center for Environmental Informatics, 2014; Wisconsin's Runoff Risk Advisory Forecast Tool, 2014). These models are generally designed in areas with wetter conditions than South Dakota, and often include state-specific conditions or parameters. Many other models designed over the years foreshadow possible runoff events and the hazards associated with them. What these various models and tools appear to have in common is an approach based on the Law of Conservation of Mass. Meaning, at a basic level, inputs minus what will stay in the watershed equal the outputs (runoff/nutrients).

Many variables factor into runoff events, such as land type, use, and weather. Having enough recorded sample data to be able to look back for similar sets of conditions in order to predict future events for watersheds is costly and time-consuming. We create and test models from large sets of historical data by interpreting patterns in the collected data and simplifying the factors to those that affect the process the greatest to generate the expected outcomes. Modeling has a range of uses, from helping both local and federal agencies determine whether land is suitable for certain uses, like farming or construction, to determining what size culverts or water spillways need to be built to help prevent water erosion or flooding.

The goal of this thesis is to better understand the base models that are being used to forecast runoff events for state agencies, but more importantly determine if they can produce effective models to represent historical data collected from smaller (field-scale) agricultural watersheds in Eastern South Dakota.

The scope of this thesis is the quantity of runoff produced by three field-scale watersheds in Eastern South Dakota under common management.

CHAPTER 2

BRIEF REVIEW OF RUNOFF MODELS

Introduction

It is too costly and time consuming to have enough records to be able to look back on all combinations of past runoff event conditions to predict how a future event will unfold. There are just too many variables affecting runoff events, such as land type, use, and weather. That is why models are created and tested from sets of historical data for select watersheds by interpreting patterns in the collected data and simplifying the factors to those that affect the process the greatest to generate the expected outcomes. Modeling runoff events has a range of uses, such as helping local and federal agencies determine whether land is suitable for certain uses like farming or construction, or to determining what size culverts or water spillways will help prevent water erosion or flooding.

Most runoff models are based on the principle of Law of Conservation of Mass, by deriving the total output (runoff) from the watershed by subtracting water retention by the soil from the total amount of precipitation added to the watershed. This paper compares four runoff models:

- Curve Number Method (CN);
- Water Erosion Prediction Project (WEPP);
- Revised Universal Soil Loss Equation, Version 2 (RUSLE II); and
- Soil and Water Assessment Tool (SWAT).

These runoff models range from a single equation and basic descriptors of the watershed, to series of equations and interactions between equations that require more finite detail of the watershed. The objective of this section is to demonstrate and compare how each model achieves its goal of simulating storm water runoff, nutrient loss due to runoff, or both. We also present published recent applications of each model, based on Google Scholar search results for each model that were published in 2018 (Google, 2004). The first 20 to 30 models for each model search result were examined, with example papers cited.

Model Description and Review

CN

The United States Department of Agriculture (USDA) Natural Resources Conservation Service's (NRCS) TR-55, Curve Number (CN) Method is the oldest of the reviewed models. The CN was developed by the USDA Soil Conservation Service in 1954 and has been revised multiple times over the years by USDA (Cronshey, 1986). The last completed revision was in 1986 with an update to the user appendix in 1999. It was originally developed from many years of runoff records for agricultural watersheds collected across the United States. With modifications and some assumptions it is also used to estimate runoff from urban watersheds (Huffman, Fangmeier, Elliot, Workman, & Schwab, 2013). As of 2017, a committee was investigating further revisions to the CN Method.

The CN is the most basic of all the reviewed models. There are few variables and mathematical operations (Equation 2.1) (Ponce & Hawkins, 1996). The model input requirements are rainfall depth of an event and curve number (CN). The CN is a function of soil type (hydrologic soil group, in particular) and land use, ground cover, and soil water conditions. Equation 2.1 predicts the volumetric runoff rate for a single event. The model assumes the watershed area serves a single purpose with consistent topography. If one of the conditions that determines the CN changes drastically within a watershed, like from a farm field to woods or flat land to rolling hills, then a new CN should be found for that part of the watershed, making two smaller watersheds. The two smaller watersheds can then be calculated separately but the totals added together to find the total amounts of runoff for the original larger watershed. This model does not address any water quality aspects of the runoff.

$$Q = \frac{\left(\left(r - 0.2\left(\frac{1000}{CN} - 10\right)\right)^2\right)}{\left(r + 0.8\left(\frac{1000}{CN} - 10\right)\right)}, \left(Q = 0 \; if \; r < 0.2\left(\frac{1000}{CN} - 10\right)\right) \qquad \text{Equation 2.1}$$

Where Q = direct surface runoff depth (in);

r = storm runoff total (in); and

CN = Curve Number.

In 2018, approximately 1500 published articles referenced the CN Method. While some articles discussed use of the CN method within research projects to validate measurements, many articles looked at opportunities to improve CN method accuracy. Many articles focused around changes to the initial abstraction ratio, $(0.2(\frac{1000}{CN} - 10))$ in Equation 2.1), which partly symbolizes soil water infiltration during the rain event. For example, Santikari & Murdoch (2018) found fewer false predictions of zero-runoff events if the initial abstraction ratio changes during the storm event. A meta-paper looked at the most common changes to the CN Method: initial abstraction ratio, water storage, and CN, and how implementing these changes might affect designing of water systems and land management recommendations (Moglen, McCuen, & Moglen, 2018). One paper reviewed whether seasons should be accounted for, which produced no statistical significance for doing so (D'Asaro, Grillone, & Hawkins, 2018). Finally, a different paper determined if the Hydrologic Soil groups should be better defined, which found moderately high runoff potential soil dominate the global distribution but no clear pattern for moderately low runoff potential soils (Ross et al., 2018).

WEPP

The Water Erosion Prediction Project (WEPP) originated in 1985. The USDA developed WEPP to replace the Universal Soil Loss Equation (USLE) as an erosion prediction technology for use by federal agencies in environmental planning and assessment (Flanagan, Gilley, & Franti, 2007). The model uses climate simulation, surface/subsurface hydrology, water balance, plant growth, and many other physical attributes in the modeling of the watershed. It also has a large database of cropland soils and vegetation scenarios, and it can model and asses a variety of land uses, climate, and hydrologic conditions (Flanagan, Ascough II, Nicks, Nearing, & Laflen, 1996).

The WEPP model bases its runoff equation on the water balance principle as the CN method, but uses the modified Green-Ampt equation (Equation 2.2) (Almedeij & Esen, 2014) to predict the amount of infiltration.

$$f(t) = K(\frac{S\Delta\theta}{F(t)} + 1) \qquad \text{Equation 2.2}$$

Where f = infiltration rate (mm h^{-1});

t = time (h).

K = hydraulic conductivity (mm h^{-1});

S = capillary suction head at the wetting front (mm);

$\Delta\theta$ = available porosity; and

F = cumulative infiltration (mm).

The WEPP model also uses a modified Yalin equation (Finkner S. C., 1989) to predict sediment transport (Equation 2.3)(Flanagan, 2015).

$$T_c = (0.635\delta(1 - \frac{1}{\beta} ln(1 + \beta)))((SG)d\rho_w{}^{\frac{1}{2}}T_s{}^{\frac{1}{2}}) \qquad \text{Equation 2.3}$$

Where T_c = sediment transport capacity (kg $\mathrm{m}^{-1}\mathrm{s}^{-1}$);

SG = particle specific gravity (unitless);

d = particle diameter (m)

ρ_w = mass density of water (kg m^{-3}); and

β and δ = dimensionless parameters.

Approximately 600 papers referenced the WEPP model in 2018. Almost all the articles pertained to using WEPP as a tool in the study to determine runoff load with few looking at actual changes to the model itself. There were mixed results when comparing WEPP, USLE or RUSLE II predictions to collected data for watersheds. One paper reviewed how saturation rates and slope of watershed affected infiltration of water in the WEPP model, along with how much the velocity of the runoff water changed with those variables (Huang et al., 2018).

RUSLE II

Developed in 1993 by the United States Department of Agriculture, the RUSLE II model is the newest model in this comparison. Its goal is to help with conservation planning but is only intended to estimate nutrient loss rates (USDA, 2016). The fact that storm erosivity and erosion are linearly proportional led to the basic idea and development of the Universal Soil Loss Equation (USLE), RUSLE II's parent model (Toy, Foster, & Renard, 2002). This idea, paired with the fact that RUSLE II implements a daily integration of the estimated erosion factors, is what gives RUSLE II more power and accuracy over USLE or RUSLE I. RUSLE II still uses the base USLE equation structure, but it is paired with process-based equations to make it better than a purely empirically-based system like the USLE (Toy et al., 2002). A process-based equation cares as much about the intermediate values (i.e. each day's sediment loss) that make up the outcome as the outcome itself (i.e. total sediment loss for the month). An empirically based system only cares about the outcome. This addition of daily time computing can be seen in Equation 2.4 where đ represents the day of the year (USDA, 2016).

$$A = S \sum (r_{đ} e_{đ} l_{đ} c_{đ} p_{đ}) \qquad \text{Equation 2.4}$$

Where A = average annual erosion (kg/hectare)

S = slope steepness (m/m);

r = rainfall-runoff erosivity factor;

e = soil erodibility factor;

l = slope length (m);

c = cover management factor;

p = support practices factor; and

đ = index for day of the year.

In 2018, approximately 150 published articles referred to RUSLE II. While some articles compared WEPP and RUSLE II, as mentioned above, many discuss using RUSLE II to validate measurements. Few articles looked at opportunities to improve

RUSLE II method accuracy. One article looked at slope tillage in China and used RUSLE II to determine which management practices worked best (Xu et al., 2018). Another article created a new soil mapping reference so RUSLE II can be used in Switzerland (Schmidt, Ballabio, Alewell, Panagos, & Meusburger, 2018; Xu et al., 2018). Finally, a published review of RUSLE II described advances over the years which allow the model to better operate and estimate erosion on a daily time step, much like WEPP can do (Kinnell, Wang, & Zheng, 2018).

SWAT

The Soil and Water Assessment Tool (SWAT) is the most complex and most advanced model of the four models. The model's goal is to help with management decisions about water, sediment, and nutrients on large, ungauged river basins (Arnold, Moriasi, et al., 2012). Development of SWAT started in the early 1990's. Unlike the other models, it is updated regularly. SWAT is made up of many models. For example: hydrology and crop growth models, Groundwater Loading Effects of Agricultural Management Systems (GLEAMS) model, the Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model, and the Environmental Policy Integrated Climate model. SWAT includes many models that are built up from other models, such as CREAMS which has aspects of CN method and Green-Ampt equation in its model (Arnold, Moriasi, et al., 2012). Models like CN and Green-Ampt were then modified by expanding their computing power, adding these models together, and/or adding new components to the models altogether (Neitsch, 2011).

One example of how SWAT uses sub-models is the Green-Ampt equation and CN method for calculating infiltration (Equation 2.2, Equation 2.1). If the rainfall data are given to SWAT in hourly totals, Green-Ampt (Equation 2.2) is used. However, if the data are given in daily rain totals the CN Method is implemented to determine infiltration (Knisel & Douglas-Mankin, 2012). Like most models, because of the modified Green-Ampt's impacts on plant growth and the movements of sediments, the basic concept of a water balance is the power plant behind the SWAT simulation (Equation 2.5) (Arnold, Moriasi, et al., 2012).

SWAT's simulated water balance/hydrologic cycle is broken into two parts. Part one is the land phase of the hydrologic cycle which controls the amount of water, sediment, and nutrient loadings, and part two is the water routing phase which defines the movement of the water and sediments (Neitsch, 2011). Equation 2.5 is part of the water balance part one and calculates soil water content over time.

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \quad \text{Equation 2.5}$$

where SW_t = final soil water content (mm);

SW_0 = initial soil water content (mm);

t = time (days);

R_{day} = precipitation per day (mm);

Q_{surf} = amount of surface runoff (mm);

E_a= evapotranspiration (mm);

w_{seep}= water entering vadose zone from the soil profile (mm); and

Q_{gw}= return flow (mm).

Approximately 2800 article referenced the SWAT model in 2018. A vast majority of the top results for the SWAT model focused around using the model within research projects to validate measurements or the setting up of the SWAT model against historically measured data for an area. For example, Tejaswini and Sathian (2018), used the SWAT model and calibrated and validated it to be used in the Kunthipuzha Basin in India.

Another paper looked at how SWAT, given limited data, would assess the impact of the Mississippi River Basin Healthy Watersheds Initiative on an Arkansas watershed (Leh, Sharpley, Singh, & Matlock, 2018). Very few articles looked at opportunities to improve SWAT model accuracy but one did research better ways to calibrate the model. In the paper authors linked SWAT and SPOTPY (Statistical Parameter Optimization Tool for Python), together to calibrate and validate SWAT model results (Camargos, Julich, Houska, Bach, & Breuer, 2018). In doing so, it gives another alternative to using SWAT's calibration and validation program, SWAT-CUP (SWAT Calibration and Uncertainty Programs).

Model Comparison

The CN and RUSLE II models require very little data. The CN only needs daily rain fall totals and a basic understanding of the watershed. For RUSLE II, a basic knowledge of watershed components like land use and soil type will produce results. The WEPP and SWAT models require everything CN method and RUSLE II do, but also, when combined with Arc GIS, you need to know how to make boundary maps and make topography maps. Along with that, SWAT is less user friendly, with any errors in user uploaded files resulting in aborted runs or unintentional incorrect output data. Another big difference is the sheer number of models that a program like SWAT has combined into its program, like CREAMS or GLEAMS models. In contrast, the CN method is its own entity. Even a midlevel model such as RUSLE II uses the CN equation as part of its model to produce a model that is more advanced than the sum of its parts alone.

Table 2.1 summarizes the four models. The CN method may not be as powerful as the other three, but what it lacks in power it makes up for by being very easy and straightforward to use; hence its use is still wide spread today. On the other hand, the SWAT model is the most powerful model and can do everything the other models can do and more. However, it is not a model that can easily be used once for some quick data output. SWAT requires a lot of forethought and inputs that must go into the model and even then, it takes training classes and/or many hours of working with the model to fully understand it and make it work. As for WEPP and RUSLE II, they are adequate representations of middle of the road models in use today. They are easy enough to understand and figure out how to use on their own, but a model like WEPP that also requires empirical input data makes it more accurate than a very simplistic equation like the CN method. In the end, it is all about determining how much and how accurate of data output is required, then picking the correct model to fit that need.

Table 2.1: Comparisons among models: CN, WEPP, RUSLE II, and SWAT.

Attribute	CN Method	WEPP	RUSLE II	SWAT
Year Developed	1954	1985	1993	Early 1990’s
Peer reviewed	No	Yes	Yes	Yes
ARCGIS Compatible	Yes	Yes	No	Yes

Table 2.1 (continued)

Land types it can be used on	Agricultural land, urban areas, forests, range lands, and grass lands (based on the NRCS-tr55 tables any land could be estimated)	Forestry, area around Fisheries, rangeland, mining studies, and agricultural land	Forestry, area around Fisheries, rangeland, mining studies, construction sites, landfills, parks, reclaimed land, military training sites, and agricultural land	Forestry, area around Fisheries, rangeland, mining studies, construction sites, landfills, parks, reclaimed land, military training sites, and agricultural land
Optimal Watershed size	Best if kept to the size that the watershed is one homogeneous area	1-1000 hectares	Best if kept to the size that the watershed is one homogeneous area	Designed for large catchments but can work on small watersheds
Runoff Calculation Frequency	Calculates daily/event total runoff	Daily	Yearly	Daily
Can be used for snowmelt runoff	No	Yes	Yes	Yes
Physical based or regression equation based	Physical	Physical	Both	Both, percent of which depends on how much empirical data is put in the model
User based data as inputs	Yes, Rainfall data	Yes, rain fall and elevation	No	Almost everything can be site specific user data if obtainable
Model provided table-based inputs	All but rain total	Majority	Majority	Empirical is used for most inputs if possible
Continuous or single event model	Single rain event is calculated at a time	Continuous modeling	Yearly sediment loss modeling	Continuous modeling
Runoff water quantity base equation	SRS-TR55 (CN Method)	Modified Green-Ampt equation	SRS-TR55 is used in model but runoff water quantity is not an output	Green-Ampt equation paired with other models
Runoff water quality base equation	None	Modified Yalin Equation	Upgraded USLE is the RUSLE II model equation	GLEAMS and CREAMS as base models

Table 2.1 (continued)

Calibration	Given known site runoff and calculated runoff differences, model can be calibrated for site over time	Given 10-20 years of extremely detailed, plot specific data, it is possible to calibrate the model for the watershed	All calibration is done by the program	Self-calibrates and user's calibration is required.
Used for prediction of past or future events	Used to predict runoff from past events or future events	Used to predict runoff and sediment from past events or future events	Used to predict yearly sediment loss for both time frames	Used to predict past runoff and water quality events or future possible events.

Summary

This chapter compared four runoff models: CN, WEPP, RUSLE II, and SWAT. Each model simulates storm water runoff, nutrient loss due to runoff, or both, using different variables and methods. Ultimately all models attempt to produce accurate representations of possible real events to help its user better understand and predict what will happen to the watershed examined.

CHAPTER 3

THE STUDIED WATERSHEDS IN EASTERN SOUTH DAKOTA

Introduction

A set of three watersheds were established near Colman, in Moody, South Dakota, as part of a long-term study of winter manure application (Singh, 2016). These watersheds are where all runoff data used in this study were collected. The goal of this chapter is to present the characteristics of these three watersheds and explain data collection methods.

Materials and Methods

Studied Runoff Watersheds

The three watersheds had areas of 2.63 ha (North watershed), 2.71 ha (East watershed), and 4.25 ha (South watershed). The North and East watersheds drained to the north and the South watershed drained to the south (Figure 3.1). All three watersheds were managed similarly in a corn-soybean rotation. The North and South watersheds received winter manure applications. These manure applications happened every winter; the upper slope on the South watershed received manure but not the lower slope and the inverse for the North watershed.

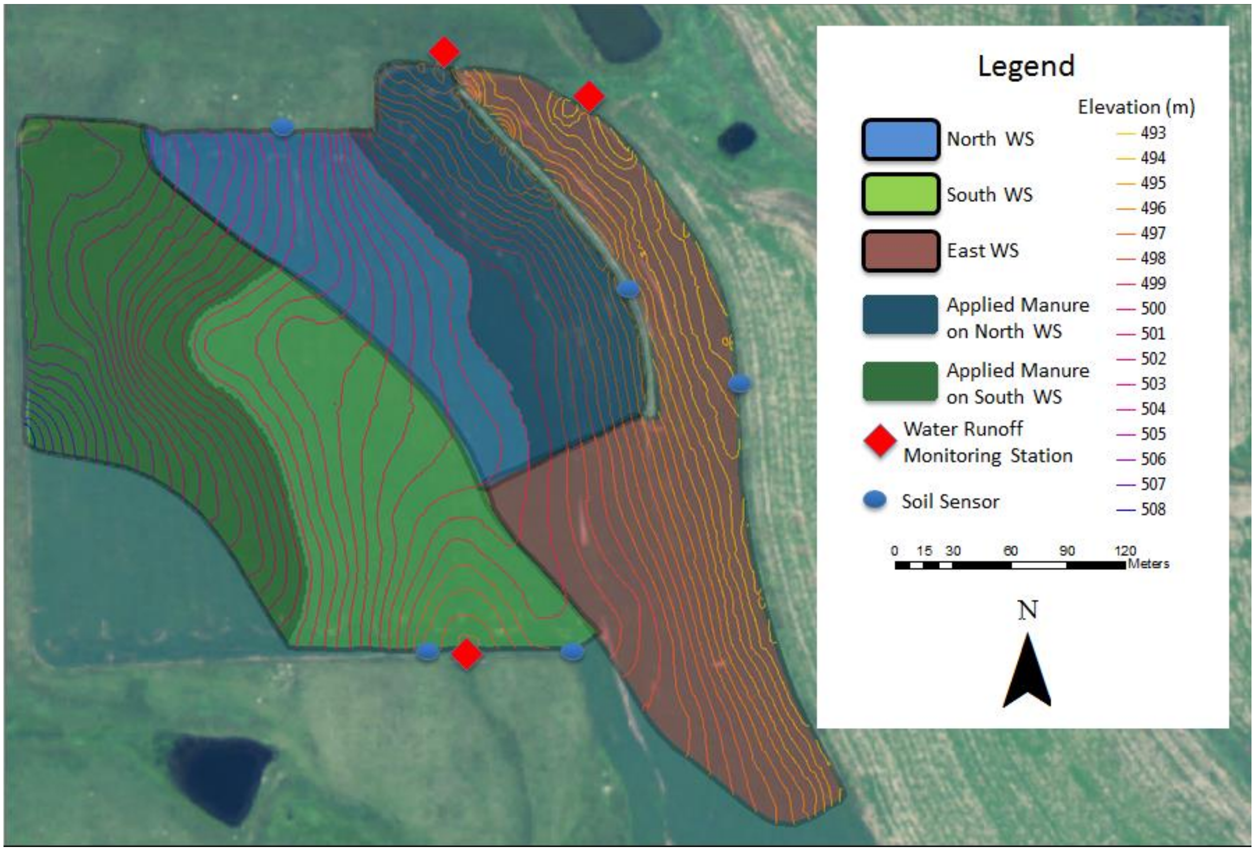

Figure 3.1: The Colman Runoff site, with runoff monitoring station for each watershed(Singh, 2016).

Runoff and Weather Measurement

Each watershed was equipped with a water runoff monitoring station and H-flume at its outlet. A Sonic Ranging Sensor (SR50A, Campbell Scientific, Logan, UT) in each flume measured the distance to the bottom of the flume, or top of the water, with a data logger converting that information into the depth of the flowing water, recording said depth every two minutes. A Tipping Bucket Rain gage (TE525, Campbell Scientific, Logan, UT) near the South flume continuously measured on-site precipitation based on the number of tips at two-minute intervals. Game cameras (Moultrie M80 Game Spy, Moultrie, Birmingham, AL) were located at each flume and took digital still frames every

15 minutes; the images helped verify the flow data. All data were downloaded after large runoff events or at least once a month (Figure 3.2).

Figure 3.2: Picture of data collection and maintenance at flume site.

Data Processing

Data were recorded as time-stamped water depth in inches. The water-depths were converted to flow rate (volume (ft^3) per time) using a flume conversion equation designed to compensate for increasing head in the flume (Brandenburg, 2013). Erroneous data like negative water heights and heights larger than possible to be recorded in the flume were removed. The digital photos were used in conjunction with the water height data to establish the start and end of each runoff event. Event start times were determined by comparing photos taken at the time of rain events to see at what depth water was seen exiting the flume. Runoff start depths/end depths were found this way to minimize any depth error in the collection system. By looking at game camera photos, the runoff starting depth for each flume site was determined, with the South, East, and North flume start depths being: 1.75, 2, and 1.27 centimeters respectively. Finally, all runoff data points were added up for the time between the start and stop points to calculate a runoff event total and finally converted into the SI units system (m^3).

All data was processed in Microsoft Excel.

Results and Discussion

Over the 2015 and 2016 seasons 249 rain events were measured. Forty-four precipitation events produced measured runoff from one or more of the watersheds. Table 3.1 shows the South watershed produced the most runoff events with 22, then the North watershed with 15, and finally the East watershed with 7.

All three watersheds are located on the same agricultural field, but differences in size and shape produced differences in number of runoff events. The South watershed is the biggest and produced the most runoff events. Even though the North and East watersheds are very similar in size, they differ in shape. The East watershed's narrow and long shape (Figure 3.1) suggests the water must run farther to reach the flume and therefore has more time for infiltration into the soil. The largest runoff event was captured at the South watershed when 18.8 cm of rain produced 1,767 m^3 of runoff. The smallest event was produced by the North watershed where 0.7 cm of rain produced 1 m^3 of runoff.

*Table 3.1. The total runoff from each watershed in 2015 and 2016. (** in the table represents a confirmed runoff event, but erroneous runoff volume recorded)*

Year	Event	Date	Precipitation total (cm)	Runoff Total (m^3)		
				South	East	North
2015	1	5/16/2015	3.38	15	0	13
	2	6/6/2015	18.85	1767	**	55
	3	6/19/2015	2.26	18	0	17
	4	6/20/2015	1.04	5	0	4
	5	6/22/2015	6.99	225	58	166
	6	7/5/2015-7/6/2015	15.09	693	137	325
	7	7/25/2015-7/26/2015	5.54	10	2	2
	8	7/28/2015	3.12	21	5	**
	9	8/6/2015	2.24	1	0	0
	10	8/9/2015	2.67	0	2	0
	11	8/18/2015 - 8/19/2015	3.33	155	0	1
2016	1	5/25/2016	1.63	2	0	0
	2	5/28/2016	7.59	49	13	29
	3	5/31/2016	1.22	1	0	0
	4	6/13/2016	1.14	1	0	0
	5	6/14/2016	0.71	**	0	1
	6	7/6/2016	1.42	1	0	0
	7	7/10/2016	3.10	7	0	3
	8	7/23/2016	2.39	4	0	1
	9	8/11/2016	2.03	8	0	0
	10	8/18/2016 - 8/19/2016	2.01	21	3	6
	11	9/5/2016	2.74	2	0	0
	12	10/4/2016	4.14	3	0	2
	13	10/6/2016	1.42	1	0	0

Summary

During the 2016-2016 growing season, a total of 44 runoff events were recorded, despite 249 rain events. Half of the runoff events were for the South watershed. Size and shape are two factors that likely contributed to differences in the occurrence and amount of runoff from each watershed for a common rainfall event.

CHAPTER 4

CURVE NUMBER MODEL ANALYSIS

Introduction

Background

The Runoff Curve Number Method (CN method) was developed in 1954 by the USDA Soil Conservation Service (SCS) as a method of estimating direct runoff from storm rainfall (Rallison & Cronshey, 1979). The method has been revised through the years and was last altered in 1993. Being simple to use and requiring basic watershed data to implement means this method has been published and still taught to future generations for more than 60 years (Blick, Kelly, & Skupien, 2004). Literature has shown varying accuracy of the CN Method in predicting runoff depending on the biome, and that the initial abstraction ratio may need variances depending of geologic and climatic settings (Ponce & Hawkins, 1996). The CN method has gained wide acceptance among engineers, designers, regulators, and land management agencies. Its use was recommended or required by 49 of 50 randomly analyzed Land Development and Storm Water Management Ordinances in Pennsylvania, based on its ease of use or a lack of anything else available to use (Fennessey & Hawkins, 2001). The objective of this study was to determine if the CN method provides an accurate estimate of runoff from three smaller watersheds in Eastern South Dakota ranging from around 2.5 to 4.5 ha.

Materials and Methods

Watersheds and Runoff Measurements

Rain data was collected from three watersheds in Moody, South Dakota, referred to as North, East and South. All three watersheds were managed similarly in a corn-soybean rotation, with South and North watersheds receiving winter manure applications. Each watershed sloped to a single runoff point which was equipped with a water runoff monitoring station and H-flume. Every two minutes water height in the flume is recorded along with rain depth and air temperature. A game camera also takes pictures of the flumes every 15 minutes and help verify the data being collected (Chapter 3). All data was processed in Microsoft Excel, cleaned, and refined to runoff totals for each rain event (Chapter 3).

Curve Number Method Runoff Estimation

The CN for cultivated agricultural lands and the hydrologic soil group for each watershed are shown in Table 4.1 (Huffman et al., 2013). Additionally, each field was designated as having row crops, contoured, and having poor hydrologic condition since there was not much observed residue left on the soil surface each year whether in soybeans or corn the previous year (Figure 4.1).

Figure 4.1: Residue left on soil surface after spring planting. The previous crop was soybean.

Table 4.1: Watershed factor and the resulting Curve Numbers.

Watershed	Hectares	Land Use	Treatment or Practice	Hydrologic Condition [A]	Hydrologic Soil Group [B]	CN
South	4.25	Row Crop	Contoured	Poor	76% group C, 24% group B	83
North	2.63	Row Crop	Contoured	Poor	61% group C, 39% group B	82
East	2.71	Row Crop	Contoured	Poor	50% group C, 50% group B	82

[A] *Derived from Soil and Water Conservation Engineering Manual, Sixth Edition (Huffman et al., 2013)*
[B] *Derived from Web Soil Survey, websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx (Soil Survey Staff, 2016).*

Data Comparison

The measured and predicted runoff (Eq 2.1) values were compared side by side for each event. Comparison consisted of the following statistics: R^2, normalized mean square error (NMSE), and linear regression slope and intercept. All three were used to evaluate how well the predicted runoff resembled the measured runoff.

Additional simulations and comparisons between measured and predicted runoff were performed to investigate alternative initial abstraction ratios, CN numbers, and hectares contributing to runoff.

Results and Discussion

Original CN Model

The CN predicted 82 runoff events over the two years for the 249 measured rain events, whereas measurements detected 44 runoff events (Chapter 3). The CN predicted 28 runoff events for the South watershed and both the North and East water sheds were estimated to have 27 events.

Figure 4.3 shows a graphical comparison of measured and calculated runoff totals. The slope of measured rainfalls with increasing precipitation amounts is considerably lower than the estimated runoff amounts for the same precipitation.

The largest predicted event occurred at the South watershed for the same rain event that produced the largest measured runoff. Using the CN, the 18.8 cm rainfall event produced an estimated 5,688 m^3 of runoff. The smallest predicted events took place for the North and East water sheds with 1.1 cm of rain predicted to produce 0.03 m^3 of runoff. There were three rainfall events with measured runoff that CN predicted to have zero runoff, and inversely 41 CN-predicted runoff events where no runoff was measured.

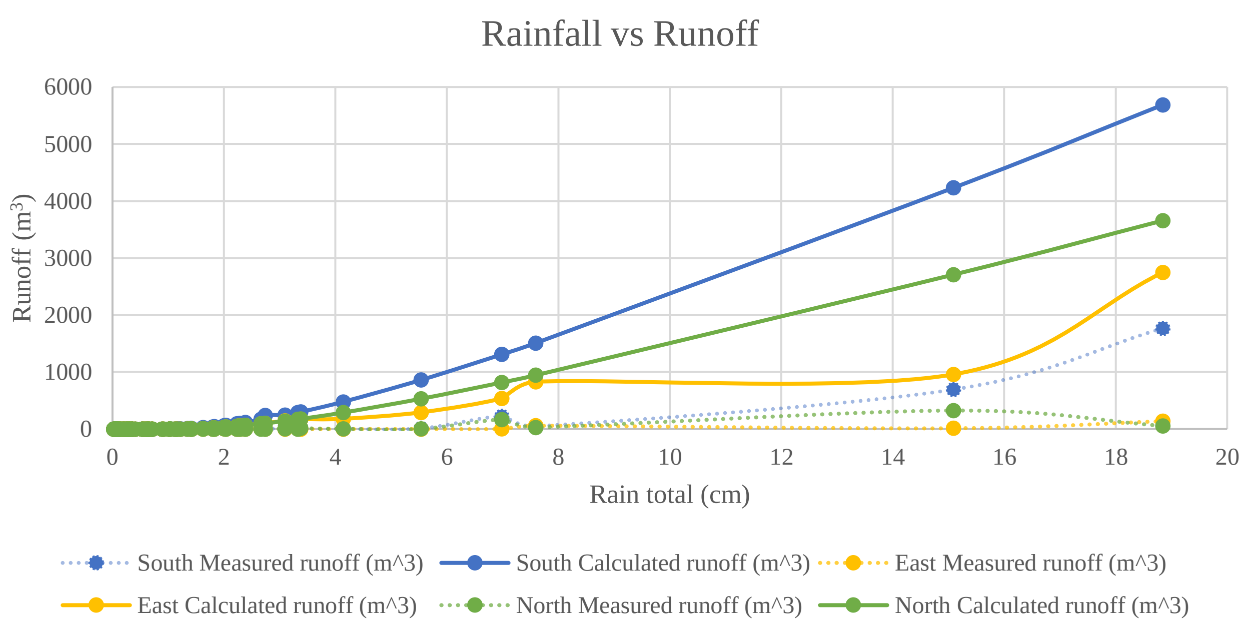

Figure 4.2: Measured and CN modeled runoff amounts for the 2015-2016 rain events.

Figure 4.2 shows the calculated runoff relative to the measured runoff for all recorded rain events in 2015-2016, for all three watersheds. The R^2 associated with the linear regression was 0.67, indicating a relationship between measured and calculated runoff. The NMSE, however, was 122, which is excessively large. When the mean of the measured was compared to the mean of the predicted it was found that, on average, the predicted runoff was 3.8 times higher than the measured.

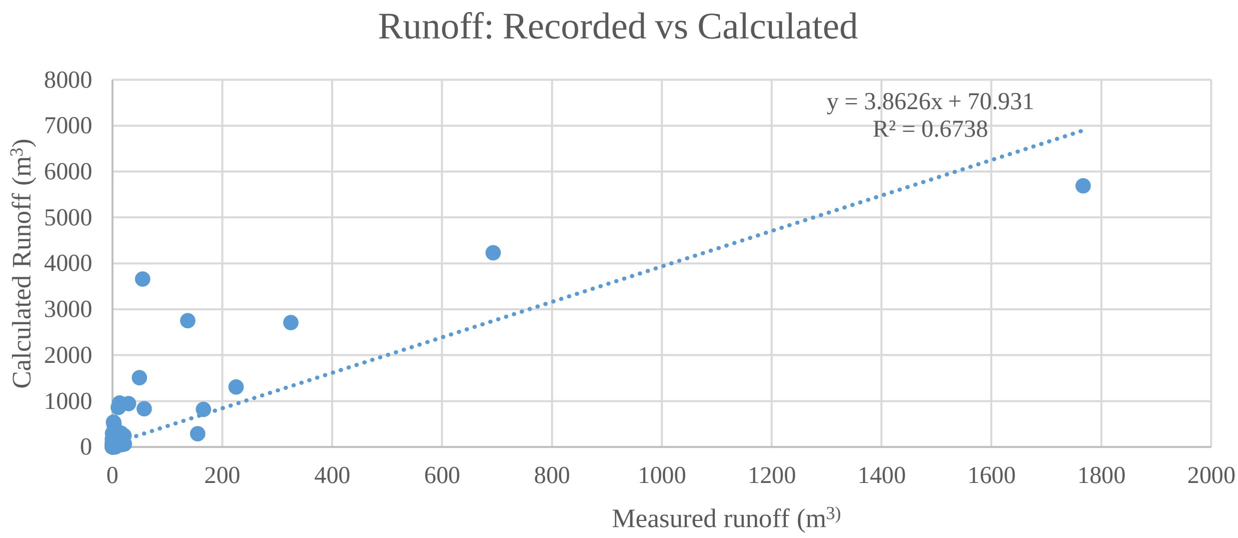

Figure 4.3: Linear regression of measured runoff compared to the predicted runoff for each rain event.

Comparison of Alternative Initial Abstraction Ratios

Changing the initial abstraction ratio of $(0.2(\frac{1000}{CN} - 10))$ in CN has been performed in many studies (Ponce & Hawkins, 1996) to improve model agreement with measurements. Table 4.2 shows initial abstraction ratios from 0.1 to 0.9 were tested in CN model. Larger initial abstraction ratio values in Eq. 2.1 theoretically means more rain infiltrated into the soil (compared to standard 0.2 ratio in Eq. 2.1) and this infiltration reduces the amount of runoff. The data shows that as a common trend that the higher the ratio was set, the lower the NMSE became and R^2 improved. Changing the initial abstraction ratio may help correct the NRCS CN equation to better predict runoff for these fields.

Table 4.2: Different levels of Curve Number Method initial abstraction ratio comparison.

Statistic	Watershed	Curve Number Method Initial Abstraction Ratio								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
NMSE	South	55	56	55	54	52	49	46	42	39
	East	478	507	529	540	540	529	514	499	483
	North	259	271	277	279	276	270	263	255	247
R^2	South	0.86	0.88	0.89	0.9	0.91	0.92	0.93	0.93	0.94
	East	0.87	0.89	0.91	0.92	0.93	0.93	0.92	0.91	0.9
	North	0.49	0.48	0.47	0.46	0.45	0.43	0.42	0.4	0.38
Mean of Measured	South	36	36	36	36	36	36	36	36	36
	East	3	3	3	3	3	3	3	3	3
	North	8	8	8	8	8	8	8	8	8
Mean of Calculated	South	225	193	169	150	136	123	113	104	95
	East	100	79	64	54	46	40	35	30	26
	North	141	120	105	93	84	76	70	63	58

Comparison of Alternative Curve Numbers

Curve numbers from 30% to 100% of the original CN for each watershed, in steps of 10%, were used to estimate runoff for each precipitation event and each watershed. A similar experiment with runoff data compared measured data to those calculated with the NRCS equation and curve number (Boughton, 1989). Similar results were also found with, in many cases, smaller CN values more accurately predicted runoff values. The best calculated results came when CN was 60% to 40% less than the CN numbers prescribed originally (Table 4.2).

Table 4.3: 10% step decreases in original Curve Number down to 30% of original CN. See Table 4.1 for original CN values.

Statistic	Watershed	% of CN Used in Calculated Runoff							
		100%	90%	80%	70%	60%	50%	40%	30%
NMSE	South	56	43	28	13	3	7	77	1490
	East	507	455	374	273	168	61	16	-
	North	271	242	200	153	105	61	46	499
R^2	South	0.88	0.91	0.93	0.95	0.96	0.97	0.98	0.85
	East	0.89	0.92	0.93	0.91	0.88	0.84	0.84	-
	North	0.48	0.45	0.42	0.37	0.32	0.26	0.16	0.02

Comparison of Alternative Effective Watershed Hectares

Finally, the total area of the watershed was adjusted with the thought that maybe only parts of the watershed produce runoff or not 100% of the watershed runoff makes it to the measuring flume (Boughton, 1989). This too was done by comparing 10% decreases in the original watershed size down to 5% (Table 4.4). The table shows decreases in NMSE for all three to 40% of their original area, with predicted optimal areas being anywhere from 30% to 5% of the actual watershed.

Table 4.4: 10% step decreases in watershed area down to 5% of the original area.

Statistic	Watershed	% of Original Watershed Hectares										
		100 %	90 %	80 %	70 %	60 %	50 %	40 %	30 %	20 %	10 %	5 %
NMSE	South	56	47	38	30	22	14	8	4	5	27	85
	East	507	452	396	341	286	230	175	121	67	18	3
	North	271	241	211	181	151	122	92	64	36	15	18

Interpretation of Comparisons and Next Steps

Manipulation of the NRCSs' CN method can produce more accurate predicted results for these Eastern South Dakota watersheds, as has been done in other regions and land use practices. Any possibly statistically acceptable model of these watersheds will come from some implementation of changes to all three changes at the same time. The many different levels of changes would take time to implement and test. This is because to compare all changes correctly would require many more runoff sites in Eastern South Dakota and many more years of data.

Summary

The goal of this study was to compare measured runoff amounts from Eastern South Dakota alongside runoff amounts calculated by the CN. Two years of measured data were collected and used as a baseline of runoff in the area. The comparison produced R2 results of 0.67 indicating a relationship between the predicted and measured runoff, but large differences in NMSE, always greater than 3, indicating over predicting of runoff by the models. Due to this, it can be concluded that the CN Method for calculating runoff on the three watersheds studied did not produce result suitable for continuing to validation of a model.

CHAPTER 5

SWAT MODEL ANALYSIS

Introduction

Background

Based on studies on the Curve Number method in Chapter 4 at the three examined watershed sites in Eastern South Dakota over the 2015 and 2016 growing season it was determined that the CN model did not predict rain event runoff satisfactory to calibrate and validate the model. The next step was therefore to test the more powerful SWAT model, in the hopes of being able to calibrate and validate a working model for the watersheds. SWAT was chosen due to its popularity and the user's ability to fine tune the program due to it being a progression based model. Progression based means that the model uses multiple steps to achieve its end output and at each of the sets adjustments can be made to the program.

The objective of this chapter was to determine if the SWAT model can accurately model the runoff from three small watersheds in Eastern South Dakota. Changes to SWAT's preprogramed evapotranspiration methods were also reviewed to improve simulations relative to measured runoff totals.

Methods and Materials

Watersheds and Runoff Measurements

All rain data was collected from Moody County, South Dakota. An agricultural field consisting of three watersheds was the location of the study site. Each watershed was managed similarly in a corn-soybean rotation with two receiving winter manure applications. Every two minutes water depth in the flume was recorded along with rain depth and air temperature. A game camera also took pictures of the flumes every 15 minutes and help verify the data being collected. All data was processed in Microsoft Excel, cleaned, and refined to runoff totals for each rain event (Chapter 3).

Data Processing

The three studied watersheds were mapped in the GIS program of ARC SWAT (ArcSWAT, 2012). Lidar data maps were also brought into ArcGIS as the model source for elevation data for the watersheds (U.S Geological Survey, 2018). The preprogramed SWAT databases of WGEN US FirsOrder and ArcSWAT SSURGO were chosen for a weather station and soil data respectively, with this weather station supplying advanced data like solar radiation and wind.

The first run of SWAT was completed using the default settings in the system and data collected at the site or known about the study site. Any other small inputs needed to run SWAT selected from the SWAT website/user manual (Arnold, Kiniry, et al., 2012). Two slope classes were set at 0 – 4.2% and 4.2 – 9999% ranges for every hydrologic response unit (HRU) and the HRU threshold was set at 10% for land use, 10% for soil class, and 10% for slope class. HRU threshold is inconsequential in a watershed of this size and could be set anywhere from 0% to 25% (Her, Frankenberger, Chaubey, & Srinivasan, 2015).

Because the watersheds were so small, and elevation changed so little over them, SWAT would not recognize a single outlet at the sites’ flumes. Without multiple outlets, SWAT would not model the entirety of the watershed. Therefore, 15 outlets were made for the North watershed, 6 for the South watershed, and 37 for the East watershed, therefore ensuring full modeling of the watersheds. Runoffs values from all outlets of a watershed were summed in Excel after model runs were completed.

Daily precipitation data was added from the closest South Dakota Cooperative Weather Station for the years of 2013 through 2016 to fill in missing daily precipitation that occurred in the winter and was not collected at the site (South Dakota State University, 2018). This was done because SWAT runs a continuous model that builds off the previous days to calculate the amount of moisture in the soil. The daily high and low temperature data collected year-round from the watershed monitoring area (Chapter 3) was used in the SWAT models. Table 5.1 shows the land use data. All 2013 and 2014 data were used as warmup for the model with 2015 and 2016 being years that were fully modeled and producing output data.

To further improve simulated runoff totals relative to measurements, a series of changes to the SWAT model settings for soil water absorption were investigated. This model parameter was also significant in CN comparisons (Chapter 4). Literature suggested that changes to the curve number (CN2), potential evapotranspiration method (IPET), and daily curve number calculation method (ICN) would have the best chance of reducing over-predictions of runoff (Guse, Reusser, & Fohrer, 2014; Lenhart, Eckhardt, Fohrer, & Frede, 2002; White & Chaubey, 2005). First, the various combinations of the preprogrammed SWAT IPET methods and ICN methods were changed to determine if there was a combination that produced closer modeled results to the observed data. Once a best combination was chosen, the SWAT model was set to that combination and the curve number was reduce by 10% to represent a more hydrophilic soil.

Whether directly or indirectly the ICN, IPET, and CN2 all allow for more water infiltration into the soil. Three of the most popular models to calculate potential evapotranspiration (IPET) are the Priestley-Taylor method, Penman-Monteith method, and the Hargreaves method (Arnold, Kiniry, et al., 2012). All three methods calculate daily soil water loss to the atmosphere, and therefore more availability to infiltrate rain water. The ICN also had a dropdown list with two choices in SWAT with either Soil Moisture Method or Evapotranspiration Method being selected and used in the modeling of the watersheds. These are calculating daily CN value as a function of soil moisture SMM (Soil Moisture Method) or calculating it as a function of plant evapotranspiration PEM (Plant Evapotranspiration method). Therefore, the ICN and IPET were tested together because IPET evapotranspiration method chosen would directly affect the ICN if Evapotranspiration method was being used in the model. Lastly, CN2 was decreased by 10% to show a more hydrophilic soil. It was not reduced any more than that because such a decrease would represent to great a change in soil hydrology, and the goal was to only determine how SWAT would react to simple decrease. Six SWAT model combinations were simulated for ICN and IPET methods combinations with a seventh SWAT model run including a 10% decrease in CN2 for the statistically best model overall of the first eight model. The seven SWAT model runs are as follows:

1. SWAT 1 Model: Penman-Monteith method + Soil Moisture method
2. SWAT 2 Model: Penman-Monteith method + Potential Evapotranspiration method
3. SWAT 3 Model: Hargreaves method + Soil Moisture method

4. SWAT 4 Model: Hargreaves method + Potential Evapotranspiration method
5. SWAT 5 Model: Priestly-Taylor method + Soil Moisture method
6. SWAT 6 Model: Priestly-Taylor method + Potential Evapotranspiration method
7. SWAT 7 Model: Penman-Monteith method + Potential Evapotranspiration method + 10% decrease in CN2

Table 5.1: Fertilizer, Planting, and Harvest dates for the two warm up years and to modeled years in SWAT for each watershed.

Year	Month	Day	Operation	Crop
2013	3	10	Fertilizer application	
2013	5	28	Plant/begin. grow	Soybean
2013	10	25	Harvest and kill	
2014	3	10	Fertilizer application	
2014	5	14	Plant/begin. grow	Corn
2014	10	25	Harvest and kill	
2015	3	23	Fertilizer application	
2015	5	28	Plant/begin. grow	Soybean
2015	10	25	Harvest and kill	
2016	4	22	Fertilizer application	
2016	5	14	Plant/begin. grow	Corn
2016	10	25	Harvest and kill	

In this study, only runoff events from the months of May through October were examined so snow melt and freezing did not affect the observed runoff at the watersheds. SWAT can produce runoff data throughout the year but due to flume design and runoff collection methods, too much error was present to compare spring runoff for rains/snow melt.

Data Comparison

For model comparison to measurements, we sorted data using the following steps. The first criteria were seeking days with rainfall events (Table 3.1). Next, only days where either the observed, the model, or both produced runoff events for a given watershed were kept for statistical comparison. This step was to keep the large number of data points where both the observed and the modeled were zero from affecting the statistical analysis.

The modeled and collected watershed data was compared using the Nash-Sutcliffe efficiency (NSE) and Percent bias (PBIAS) as per the Meta paper ‘Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations’ (Moriasi et al., 2007). A CN (Eq. 2.1) comparison was also included. Satisfactory results for the NSE are 0.50 to 1 and a PBIAS of -25 to 25, with a perfect model being 1 and 0 for NSE and PBIAS, respectively.

Results and Discussion

Over the 2015 and 2016 seasons 249 rain events were measured. Forty-four precipitation events produced measured runoff and these 44 events were unevenly divided among the three watersheds.

For the 2015-2016 study periods, the SWAT 1 Model predicted the three watersheds would produce 89 runoff events, over doubling that of the actual number of events recorded. The last iteration (SWAT 7 Model) only predicted 27 runoff events.

Along with a large decrease in the number of runoff events the SWAT 7 Model produced the best statistics for all three watersheds out of all the models examined (Table 5.2).

Appendix A shows all rain event for 2015 and 2016 along with all collected and modeled runoff events.

Table 5.2: Statistical tests for the observed vs modeled data using the CN method and SWAT iterations 1-7.

NSE (Nash-Sutcliffe efficiency) and PBIAS (Percent bias) of Observed Data vs Modeled Data, and number (n) of runoff events per model

Model	South Watershed			East Watershed			North Watershed		
	NSE	PBIAS	n	NSE	PBIAS	n	NSE	PBIAS	n
CN Model	-8.04	-432	28	-266.66	-2122	20	-114.09	-1219	21
SWAT 1 Model (Penman-Monteith method + Soil Moisture method)	-2.37	-270	31	-311.21	-2484	29	-92.45	-1183	30
SWAT 2 Model (Penman-Monteith method + Potential Evapotranspiration method)	-0.67	-162	33	-152.74	-1565	28	-47.44	-778	30
SWAT 3 Model (Hargreaves method + Soil Moisture method)	-2.27	-262	19	-300.78	-2404	19	-91.31	-1160	19
SWAT 4 Model (Hargreaves method + Potential Evapotranspiration method)	-1.16	-199	36	-199.35	-1871	34	-61.45	-909	34
SWAT 5 Model (Priestly-Taylor method + Soil Moisture method)	-3.73	-325	22	-345.24	-2739	20	-123.16	-1362	20
SWAT 6 Model (Priestly-Taylor method + Potential Evapotranspiration method)	-1.85	-233	16	-203.23	-1941	16	-78.96	-1013	16
SWAT 7 Model (Penman-Monteith method + Potential Evapotranspiration method + 10% decrease in CN2)	0.63	-59	9	-30.13	-772	9	-19.74	-447	9

Table 5.2 also shows an improvement in most statistics for SWAT-based model compared to the CN Model. Some exceptions are the SWAT 5 Model for the East and North watersheds, and the SWAT 1 and 3 Models for the East watershed. For all three watersheds, statistics improved from SWAT 1 Model to SWAT 2 Model. The NSE improved from -2.37 to -0.67 for the South watershed, -311.21 to -152.74 for the East watershed, and -92.45 to -47.44 for the North watershed. SWAT 2 Model was the best statistically when comparing the CN model and SWAT 1-6 Models.

SWAT 2 Model was proven to the closest to acceptable NSE's and PBIAS's of 0.5 and plus or minus 25 respectively so a 10% decrease in CN2 was added to the model to represent an increase in soil water holding capacity, thus creating SWAT 7 Model. The new SWAT 7 Model provides the best overall statistics by far with improvements for all watersheds in both NSE and PBIAS. The trend can be seen in figure 5.1A and 5.1B from the CN model to the SWAT 1 Model, with the only decrease in statistics seen for the East watershed. SWAT 7 Model produces a passing result with an NSE of 0.63 for the South watershed, with a passing being anything above 0.5 (Figure 5.1A).

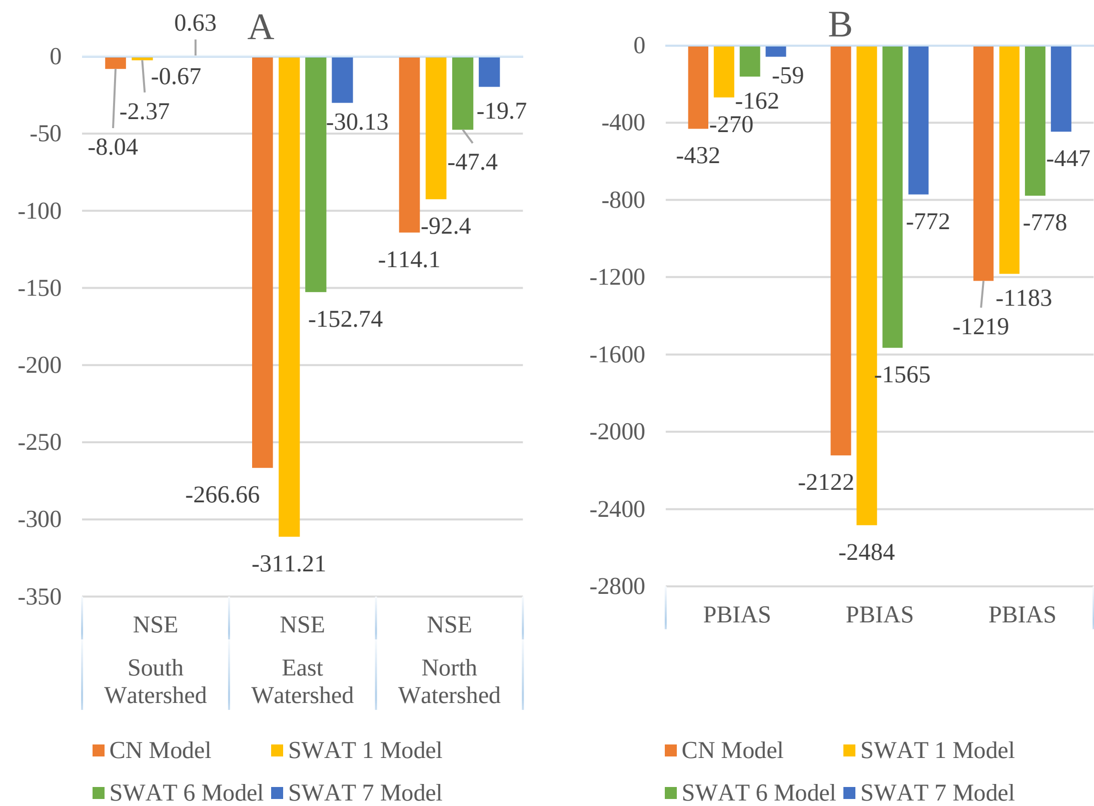

Figure 5.1: The NSE (Nash-Sutcliffe efficiency) (5.1A) and PBIAS (Percent bias) (5.1B) between modeled (various models) and measured runoff amounts for the three study watersheds.

There was an uneven number of runoff events for rainfalls less than and greater than 2 cm. There is also a theoretical inflection point at low rainfalls where the soil infiltration rate is exceeded, and runoff occurs. A rainfall of 2.01 cm is the first record of all three watersheds producing runoff for a rain event. Only four 1 to 5 m^3 runoff events combined took place for rainfall from 0 – 2 cm. Based on these two observations, the models' runoff estimates were split between rainfalls of 2.01 cm and above and 2 cm and below. Tables 5.3 and 5.4 show that 0 – 2 cm rainfalls have an unproportioned effect on all three watersheds statistics despite very few runoff events in this rainfall range. North and East watersheds only recorded 3 and 2 runoff events for the model and rainfall, respectively. Table 10 show all three watersheds have the poorest NSE and PBIAS for low rainfall events, with statistical decreases of 1000% or more in some cases. Note, no decrease was seen by the North watershed for the CN model and in general the CN model saw not as great of effect as the other models. With the exclusion of the rain events below 2 cm, the overall statistics in table 5.3 can be seen to be better than the same modeling settings in table 5.2 including the smaller rain events. Due to the skewing power of the small rain events, figures 5.2 to 5.4 focus on the 2.01 cm and greater rainfall where 85% of the runoff events for SWAT 7 Model occur.

Table 5.3: Statistical tests for the observed vs modeled data for best SWAT model iterations and the original CN model, greater than 2 cm rainfall.

NSE (Nash-Sutcliffe efficiency) and PBIAS (Percent bias) of Observed Data vs Modeled Data for rainfalls greater than 2 cm and (n) number of runoff events per model

Model	South Watershed			East Watershed			North Watershed		
	NSE	PBIAS	n	NSE	PBIAS	n	NSE	PBIAS	n
CN Model	-7.08	-429	18	-252.61	-2119	18	-103.31	-1227	18
SWAT 1 Model (Penman-Monteith method + Soil Moisture method)	-1.98	-259	16	-261.68	-2377	15	-76.33	-1153	15
SWAT 6 Model (Priestly-Taylor method + Potential Evapotranspiration method)	-0.47	-158	11	-122.99	-1525	11	-41.07	-769	11
SWAT 7 Model (Penman-Monteith method + Potential Evapotranspiration method + 10% decrease in CN2)	0.67	-56	8	-24.92	-744	8	-17.42	-440	8

Table 5.4: Statistical tests for the observed vs modeled data for best SWAT model iterations and the original CN model, less than 2.01 cm rainfall.

NSE (Nash-Sutcliffe efficiency) and PBIAS (Percent bias) of Observed Data vs Modeled Data for rainfalls less than 2 cm and number (n) of runoff events per model

Model	South Watershed			East Watershed			North Watershed		
	NSE	PBIAS	n	NSE	PBIAS	n	NSE	PBIAS	n
CN Model	-62.63	-1248	10	N/A 0 error	N/A 0 error	2	-0.33	-127	3
SWAT 1 Model (Penman-Monteith method + Soil Moisture method)	-917.99	-3341	15	N/A 0 error	N/A 0 error	14	-1006.35	-5384	15
SWAT 6 Model (Priestly-Taylor method + Potential Evapotranspiration method)	-279.77	-1291	5	N/A 0 error	N/A 0 error	5	-179.99	-2032	5
SWAT 7 Model (Penman-Monteith method + Potential Evapotranspiration method + 10% decrease in CN2)	-96.97	-872	1	N/A 0 error	N/A 0 error	1	-43.98	-1426	1

Figures 5.2, 5.3, and 5.4 show the resulting runoff events for rainfalls greater than 2.01 cm data from the cleaning process, and closer examination for rainfall greater than 4.5 cm. Each figure shows the recorded runoff, the SWAT 1 Model, and the statistically best model SWAT 7 Model, for each watershed. As is shown in the NSE and PBIAS in table 5.2, the SWAT 7 Model produces closer trending lines to the collected data than that of the SWAT 1 Model. For rainfall measurements of 4.5 cm to 8 cm, the SWAT 7 Model much more closely followed trends in the collected data then that of the SWAT 1 Model. For the larger rainfalls, 4 cm – 19 cm, the SWAT 7 Model seems to most closely follow the collected data. Even with SWAT 7 trending closer to the collected data than

any other model, it still over-predicts more runoff than was collected for almost every rainfall event, similar to other model iterations. In taking a closer look at all three watersheds from 2 cm – 4.5 cm in figure 5.2B, 5.3B, and 5.4B much less of a linear trend can be seen between the collected and modeled data. These figures show little to no trends taking place between the runoff values at each rainfall, with the only resemblance of matching data point taking place where collect and modeled data produce zero runoff.

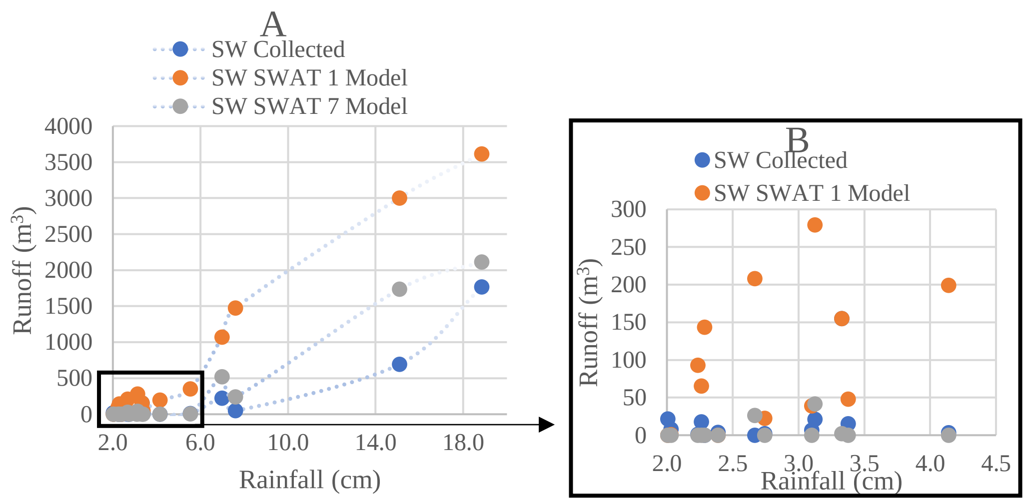

Figure 5.2: South watershed (SW) collected, SWAT 1 modeled, and SWAT 7 modeled runoff for every 2015-2016 rain events of; 2 cm or greater for figure 5.2A and 2 cm to 4.2 cm for figure 5.2B.

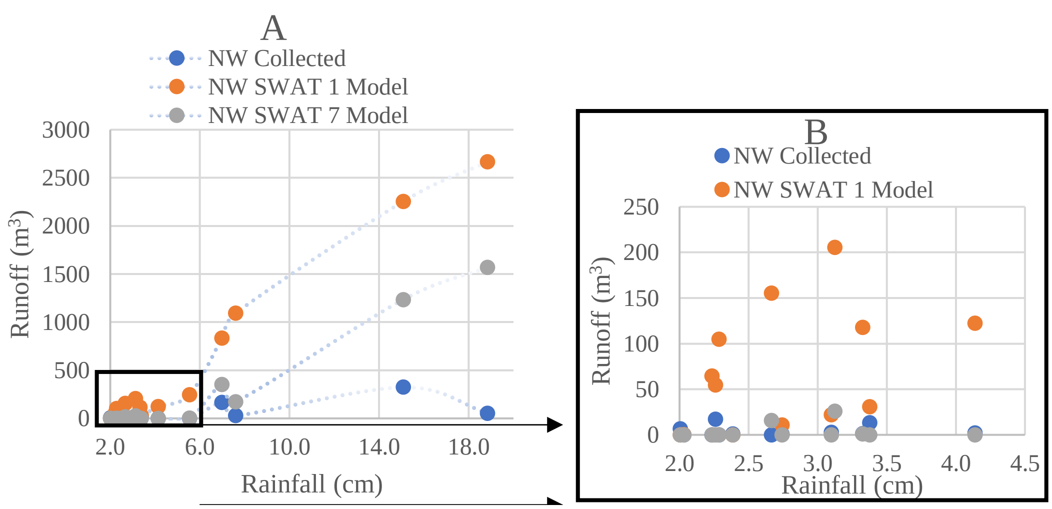

Figure 5.3: North watershed (NW) collected, SWAT 1 modeled, and SWAT 7 modeled runoff for every 2015-2016 rain events of; 2 cm or greater for figure 5.3A and 2 cm to 4.2 cm for figure 5.3B.

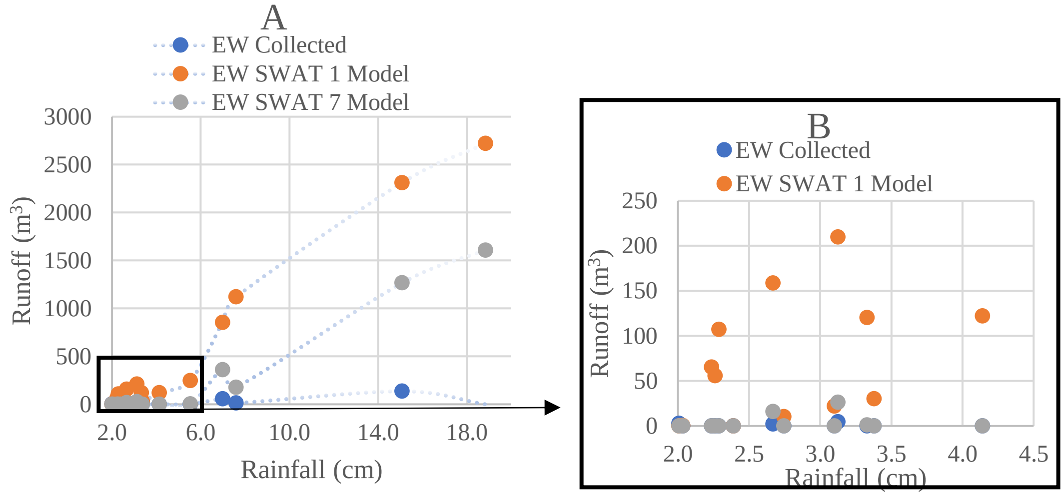

Figure 5.4: East watershed (EW) collected, SWAT 1 modeled, and SWAT 7 modeled runoff for every 2015-2016 rain events of; 2 cm or greater for figure 5.4A and 2 cm to 4.2 cm for figure 5.4B.

The South watershed had the best overall statistics and closest trending lines to collected runoff (figure 5.2A). All three watersheds had results closer to satisfactory for the larger rainfalls. Given the fact that SWAT is more conducive to larger watersheds and was created to work best modeling hundreds or thousands of hectares, statistical standards based off these larger watersheds may be too restrictive for small watersheds, especially for smaller rainfalls. Over the two years studied, 19 of the 44 runoff events collected produced less than 10 m^3 of runoff, with the rainfalls that produced said runoff ranging from 0.71 cm – 5.54 cm. To put this in perspective, for a single small rain event where the collected runoff is 2 m^3 and the model predicts 8 m^3, this results in an NSE of 0 and a PBIAS of -300. Given this, larger statistical skewing is more likely for small watersheds since smaller watersheds produce smaller runoff totals and have a greater possibility of drastically throwing off statistical results. As is shown in the example, a 6 m^3 difference at lower runoff rates shows very unfavorable results for PBAIS, whereas a 6 m^3 difference in the hundreds of m^3 would produce excellent statistics. A rain event producing 100 m^3 of collected runoff and 106 m^3 of modeled runoff would equal an NSE of 0 but a PBAIS of -5.7, an acceptable PBAIS results.

Summary

The SWAT 7 Model was able to produce the best model results for all watersheds and a satisfactory NSE (0.67) for the South watershed at higher rainfalls, 2cm and above. For rainfalls above 4 cm there is consistent trending with the collected data and the best modeled comparison results. The SWAT model still must overcome struggles in the 2 cm to 4.2 cm rainfalls with hardly any commonality between collected and modeled for those rainfall depths. Overall, SWAT can model the watersheds to some degree, given its ability to trend with the collected data at higher rainfalls, especially when changes were made to areas like the IPET, ICN, and CN2 which improved the modeling results. Changes to the SWAT inputs improved the results but no changes have yet produce a model that works for all the watersheds to a satisfactory degree.

CHAPTER 6

CONCLUSIONS

What We Know Now

Thus far, neither the CN or SWAT models was able to produce an overall acceptable model for the small Easter South Dakota watersheds in this study. The SWAT modeling process does show promise to be able to produce a satisfactory model with an acceptable NSE result for the North watershed. Both models could be manipulated to improve model improvements relative to measurements, but no ideal manipulation was found for all situations.

How to Further the Research?

With the moderate success SWAT showed in producing a working model and the limited possibilities left to change in the CN model, future testing should be focused on the SWAT model. The SWAT model's biggest hurdle to success is the model over estimation of runoff at almost every rainfall point. To overcome this problem three different possible solutions are laid out as follows.

1. To model the entire watersheds in the SWAT model, multiple outlets were created in the model for each site. This insured full coverage of the watersheds but may have inadvertently resulted in SWAT over producing runoff that may have otherwise infiltrated into the soil. The East watershed had the most outlets due to its shape and over predicted runoff by the greatest amount. The East watershed had the highest NSE and PBIAS. With a possible solution to this would be cut the

number of outlets by 10-25% while still achieving maximum coverage and see if model statistics improve.

2. Although SWAT is designed to be able to work on small watersheds, it was designed for use on much larger watersheds than were tested. Given this, working the test area as one large watershed my produce better results for modeling through SWAT. Combining all the watersheds would increase the size to a watershed almost three times bigger than all the watersheds alone. This would likely smooth out the differences seen between the watersheds, such as their differences in shape and size.
3. Given the manure applied to the field every year along with the healthy soils that cover the watersheds there may be a higher organic matter than SWAT gives credit for. A 10% decrease in CN produced a better model, harking to possible better soil hydrology than is being modeled. This can also partly explain why modeled runoff is usually higher than the collected as well as some of the differences seen in the collected vs modeled data. A better understanding of the soil may help produce better results.

Summary

The goal of this study was to see if CN or SWAT models would be able to model the studied testing sites in eastern South Dakota, in hopes to better understand what problems may be faced when performing such a task. In doing so, it would provide a base for being able to more efficiently predict how rain storms will affect agricultural land in the region, as well as be able to guide other projects to better understand problems that may be faced when modeling Ag lands in the area. No model, or iteration thereof, may have successfully modeled all three watersheds but the problem and possible solutions to this fact have now been laid out.

APPENDIX

Appendix A: Runoff data for all SWAT models, the CN model, and the measured model. For every rain event in 2015-2016 (shaded numbers signify zero runoff).

Rain (cm)	Runoff (m^3)																										
	Collected Runoff			CN Model			SWAT 1			SWAT 2			SWAT 3			SWAT 4			SWAT 5			SWAT 6			SWAT 7		
				CN Model			Penman/Monteith method + Soil Moisture method			Penman/Monteith method + Potential Evapotranspiration method			Hargreaves method + Soil Moisture method			Hargreaves method + Potential Evapotranspiration method			Priestly-Taylor method + Soil Moisture method			Priestly-Taylor method + Potential Evapotranspiration method			Penman/Monteith method + Potential Evapotranspiration method + 10% decrease in CN2		
	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North
18.85	1767	**	55	5664	3317	3322	3616	2721	2667	2758	2100	2049	3629	2734	2675	3071	2339	2283	4356	3309	3232	3693	2811	2741	2114	1609	1570
15.09	693	137	325	4209	2395	2408	3003	2313	2256	2674	1937	1890	2943	2275	2218	2853	2117	2064	3168	2386	2331	2791	2034	1986	1735	1266	1236
7.59	49	13	29	1494	744	760	1473	1120	1093	453	338	329	1484	1125	1097	573	426	415	1507	1145	1117	684	512	499	241	178	174
6.99	225	58	166	1295	630	646	1073	856	834	1128	811	793	1043	833	811	1144	870	845	1305	995	970	1401	958	937	523	362	354
5.54	10	2	2	850	383	397	353	248	246	119	76	75	304	214	212	219	137	135	361	246	243	155	102	100	6	3	3
4.14	3	0	2	470	185	196	199	122	122	21	16	15	191	117	117	42	32	31	279	181	180	86	65	63	0	0	0
3.38	15	0	13	293	101	109	48	30	31	0	0	0	56	36	37	5	3	3	173	119	118	33	25	24	0	0	0
3.33	155	0	1	282	96	103	155	120	118	148	93	92	109	85	83	244	173	169	157	119	116	262	174	170	2	1	1
3.12	21	5	**	241	77	84	279	210	205	203	138	135	251	189	185	309	206	202	288	212	207	254	176	172	42	26	26
3.10	7	0	3	235	75	82	39	22	22	0	0	0	45	26	26	0	0	0	49	29	29	0	0	0	0	0	0
2.74	2	0	0	169	47	52	23	10	11	0	0	0	19	9	9	0	0	0	41	21	21	0	0	0	0	0	0
2.67	0	2	0	156	42	47	208	159	155	165	112	109	175	132	129	236	166	162	218	164	160	259	179	175	26	16	16
2.39	4	0	1	111	25	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2.29	0	0	0	96	19	23	144	107	105	0	0	0	148	109	106	0	0	0	154	115	112	4	2	2	0	0	0
2.26	18	0	17	93	18	22	66	56	55	42	31	30	63	54	53	50	38	37	137	107	104	115	70	69	0	0	0
2.24	1	0	0	89	17	20	93	65	64	25	15	15	83	59	58	67	45	44	106	74	72	60	39	39	0	0	0
2.03	8	0	0	63	9	11	1	0	0	0	0	0	1	0	0	0	0	0	4	2	2	0	0	0	0	0	0
2.01	21	3	6	60	8	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.83	0	0	0	41	3	5	0	0	0	0	0	0	0	0	0	0	0	0	10	5	5	0	0	0	0	0	0
1.80	0	0	0	38	3	4	0	0	0	0	0	0	1	0	0	0	0	0	32	22	22	0	0	0	0	0	0
1.63	2	0	0	23	0	1	66	49	48	0	0	0	72	53	52	0	0	0	75	55	54	0	0	0	0	0	0

Appendix A continued

Rain (cm)	Runoff (m³)																										
	Collected Runoff			CN Model			SWAT 1			SWAT 2			SWAT 3			SWAT 4			SWAT 5			SWAT 6			SWAT 7		
				CN Model			Penman/Monteith method + Soil Moisture method			Penman/Monteith method + Potential Evapotranspiration method			Hargreaves method + Soil Moisture method			Hargreaves method + Potential Evapotranspiration method			Priestly-Taylor method + Soil Moisture method			Priestly-Taylor method + Potential Evapotranspiration method			Penman/Monteith method + Potential Evapotranspiration method + 10% decrease in CN2		
	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North
1.42	1	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.42	1	0	0	10	0	0	3	1	1	0	0	0	3	1	1	0	0	0	12	7	7	0	0	0	0	0	0
1.40	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
1.35	0	0	0	6	0	0	24	18	17	5	2	2	15	11	11	19	13	12	26	18	18	18	10	10	0	0	0
1.22	1	0	0	2	0	0	33	24	24	0	0	0	32	24	23	0	0	0	32	24	24	0	0	0	0	0	0
1.17	0	0	0	1	0	0	17	11	11	0	0	0	20	14	13	0	0	0	20	14	14	0	0	0	0	0	0
1.14	1	0	0	1	0	0	13	8	8	0	0	0	15	10	10	0	0	0	15	10	10	0	0	0	0	0	0
1.12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.04	5	0	4	0	0	0	4	4	4	4	2	3	4	4	4	5	3	4	20	16	16	38	18	20	0	0	0
1.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.02	0	0	0	0	0	0	4	3	3	0	0	0	2	1	1	5	2	3	6	4	4	5	2	2	0	0	0
0.91	0	0	0	0	0	0	4	2	2	0	0	0	5	3	3	0	0	0	5	3	3	0	0	0	0	0	0
0.89	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
0.71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.71	**	0	1	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	1	1	1	0	0	0	0	0	0
0.66	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.66	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0

Appendix A continued

Rain (cm)	Runoff (m^3)																										
	Collected Runoff			CN Model			SWAT 1			SWAT 2			SWAT 3			SWAT 4			SWAT 5			SWAT 6			SWAT 7		
				CN Model			Penman/Monteith method + Soil Moisture method			Penman/Monteith method + Potential Evapotranspiration method			Hargreaves method + Soil Moisture method			Hargreaves method + Potential Evapotranspiration method			Priestly-Taylor method + Soil Moisture method			Priestly-Taylor method + Potential Evapotranspiration method			Penman/Monteith method + Potential Evapotranspiration method + 10% decrease in CN2		
	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North
0.58	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	0	0	2	1	1	0	0	0	0	0	0
0.56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.36	0	0	0	0	0	0	1	1	1	0	0	0	1	0	0	1	1	1	1	1	1	1	0	0	0	0	0
0.36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.25	0	0	0	0	0	0	5	3	3	1	1	1	5	3	3	2	1	1	5	3	3	2	1	1	1	0	0
0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.15	0	0	0	0	0	0	2	1	1	0	0	0	3	2	2	0	0	0	8	5	5	2	1	1	0	0	0

Appendix A continued

Rain (cm)	Runoff (m^3)																										
	Collected Runoff			CN Model			SWAT 1			SWAT 2			SWAT 3			SWAT 4			SWAT 5			SWAT 6			SWAT 7		
				CN Model			Penman/Monteith method + Soil Moisture method			Penman/Monteith method + Potential Evapotranspiration method			Hargreaves method + Soil Moisture method			Hargreaves method + Potential Evapotranspiration method			Priestly-Taylor method + Soil Moisture method			Priestly-Taylor method + Potential Evapotranspiration method			Penman/Monteith method + Potential Evapotranspiration method + 10% decrease in CN2		
	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North	South	East	North
0.13	0	0	0	0	0	0	173	107	116	131	82	89	173	108	117	146	91	99	207	130	140	177	111	120	100	63	68
0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.08	0	0	0	0	0	0	6	3	4	2	1	1	5	3	3	4	2	3	6	3	4	3	2	2	0	0	0
0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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