A modeling approach for operational flash flood forecasting for small-scale watersheds in central Iowa

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A modeling approach for operational flash flood forecasting for small-scale watersheds in central Iowa

by

W. Scott Lincoln

A thesis submitted to the graduate faculty in partial fulfillment of the requirements for the degree of

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Program of Study Committee:
Kristie Franz, Major Professor
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Dedication

I dedicate this report to my close friends and family, who, with their loving support and unconditional encouragement, made this work possible.
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Abstract

National Weather Service (NWS) forecasters currently have access to a limited set of models that may not be suitable for all Iowa basins or forecasting situations, such as small, fast responding streams. Flexible modeling systems that allow model configurations to change according to the watershed characteristics may provide useful predictive information to supplement existing forecast products. The United States Army Corps of Engineers (USACE) Hydrologic Engineering Center’s Hydrological Modeling System (HEC-HMS) was examined for operational streamflow forecasting using two watersheds in central Iowa. The Green & Ampt equation was used for the infiltration component with soil parameters derived from the Water Erosion Prediction Project (WEPP) model run at Iowa State University. Observed precipitation data was obtained from the city of Ames’ flash flood Alert network and radar precipitation estimates were obtained through the University of Iowa’s Hydro-NEXRAD project. Calibration and verification of the modeling system was done through an operational perspective to test the model’s applicability at NWS Weather Forecast Offices (WFO). Model development was done using observed precipitation and was conducted in several stages. The average peak timing error and average discharge peak error were reduced from 5.3 hours to 3.0 hours and 46% to 25%, respectively, from the first to the last calibration attempt. The calibrated model was tested with bias corrected NEXRAD precipitation estimations, which were derived using the Constant Altitude Plan Position Indicator (CAPPI) algorithm. The bias correction scheme was computed and applied at the watershed scale. When used as input to the HEC-HMS model, the NEXRAD precipitation estimates increased the peak timing error to 8.8 hours, but the discharge peak error decreased to 20%. 
1 Introduction

Adding new modeling tools to the current National Weather Service (NWS) hydrologic forecasting system is difficult because the software structure, which has been continually developed over several decades, is very complex. Therefore, forecasters currently have access to a limited set of models that may not be suitable for all Iowa basins or forecasting situations. There are three main streamflow forecast tools available to NWS hydrologists. (1) The Sacramento Soil Moisture Accounting (SAC-SMA) model (Burnash et al., 1973) is the primary forecasting model used by the NWS River Forecast Centers (RFCs) for generation of daily to seasonal streamflow predictions. The commonly-used 6-hour SAC-SMA modeling time step disregards basin-specific hydrologic response times and can fail to capture peak streamflow in small, fast-responding watersheds. The SAC-SMA has been transitioned to run at an hourly time step for only a few watersheds, such as the Blue River in the Missouri Basin (NWS Hydrology Laboratory, 2006). (2) The Site Specific model (SSM) was designed for small headwater basins, which are not typical of many central Iowa forecast basins (Shelton & May, 1996; Noel & Dobur, 2003). Experience has shown that the SSM is not accurate for forecasting discharge from basins with tributaries in the Central Iowa region, particularly when initial soil conditions are dry and runoff is delayed (K. Tebben, City of Ames, personal communication 2007; M. Baker, NWS, personal communication, 2007). (3) Flash Flood Guidance (FFG) is used to generate watches and warnings for a specific location based on antecedent moisture conditions and current rain rates (NRC, 2005). However, FFG is based on historical observations of streamflow events and is seldom updated over time (Ntelekos et al., 2006). A recent National Research Council
(NRC) panel concluded that the scientific basis that underpins flash flood forecasting could be improved through the use of modern modeling techniques (NRC, 2006).

Currently underway in the NWS is an effort to modernize the software infrastructure used in streamflow forecasting. Recently, the Community Hydrologic Prediction System (CPHS) has been proposed (Schaake et al. 2006) which will have an open software infrastructure allowing new components to be “plugged in” to the forecasting system more easily. CPHS will allow more flexibility in the various stages of the modeling process at NWS RFCs, including the ability to add multiple community models (NWS Office of Hydrologic Development, 2009). Using multiple models will allow forecasters to view ensembles of predicted streamflow, aiding in their forecasting by showing potential uncertainty and providing multiple models that may be better for different situations. Successful testing of various streamflow models for flash flooding situations may justify their implementation into the CPHS infrastructure as well, thus increasing the number of tools available to RFC forecasters.

In this study, the U.S. Army Corps of Engineers Hydrologic Engineering Center’s Hydrologic Modeling System (HEC-HMS) (USACE, 2006) is evaluated for use in flood prediction in the Des Moines Weather Forecast Office (DMX) region. The highly flexible HEC-HMS allows the watershed to be modeled in a distributed manner, accepts data in time increments of minutes to hours, and runs easily on a PC platform (USACE, 2006). With the advent of CPHS, the ability to interface the HEC-HMS with the NWS forecasting tools at the RFCs may be possible in the future. More importantly, the ability to run the HEC-HMS on a PC makes the model a viable option for the NWS Weather Forecast Offices (WFOs).
Based on prior studies and known applications, the HEC-HMS shows promise for use in reliable operational flood forecasting at NWS weather forecast offices. The HEC-HMS is being implemented by the US Army Corps of Engineers to predict reservoir inflow along the Red River in North Dakota and Minnesota (Hu et al., 2006). Hu et al. (2006) found that the model provided reasonable streamflow simulations for a range of soil moisture conditions in their study basin. Preliminary results from the application of the HEC-HMS and NEXRAD rainfall data for the San Antonio River basin, showed a reasonable match between modeled and observed hydrograph peaks and shape (Knebl et al., 2005). The model has also been successfully applied for flood monitoring by the City of Ames, Iowa for over ten years (K. Tebben, City of Ames, personal communication, 2006). To our knowledge, DMX will be the first NWS forecast office to evaluate the HEC-HMS for operational flood forecasting and to assist in developing an application framework for the model.

Most studies involving the HEC-HMS have focused on re-creation of past flood events or parameter sensitivity analysis. The most common setup of the HEC-HMS when applied for streamflow forecasting is the soil moisture accounting infiltration model using gridded NEXRAD precipitation estimates. The soil moisture accounting infiltration model available in the HEC-HMS is similar to the SAC-SMA model used by RFCs, but is simpler and has fewer parameters. A study by Markar et al. (2004) compared the “goodness-of-fit” of five different streamflow models to the observational record over a four year calibration period and a two year verification period using the soil moisture accounting method. Results from Markar show that the HEC-HMS performed best in one of the two basins and the second-best results in another. The model also performed the best out of all the models when
looking at error in total flood volume. Although the soil moisture accounting option produced satisfactory results in these studies, this method requires the estimation/calibration of 18 conceptually-based parameters in the infiltration model, the highest requirement of any infiltration method available in the HEC-HMS. Fewer parameters and more physically-based parameters were desired in this study to ease model calibration and use. In addition, the soil accounting method uses a modeling approach that is very similar to the SAC-SMA, and would therefore be somewhat redundant.

There are several ease-of-use advantages to choosing the HEC-HMS model for this study. The graphical user interface (GUI), the ability to download the HEC-HMS freely from the internet on a PC-platform, and the ability to model a watershed in a semi-distributed manner, are all particularly beneficial. In the semi-distributed modeling approach, outputs from multiple watersheds are computed separately and combined sequentially from upstream to downstream. The distributed approach will allow sub-basin conditions to be modeled and monitored, with each catchment calibrated to one streamflow gauge. The HEC-HMS is also very versatile, and can be adjusted to use a number of different infiltration methods and precipitation inputs. Bedient et al. (2007) showed the HEC-HMS’ versatility by using it in conjunction with hydraulic models during a tropical storm and was able to reproduce significant tailwater conditions in southern Texas. Finally, the HEC-HMS can be run on a sub-hourly basis, allowing the user to tailor the simulation timestep to the basin hydrology. In this study, we used a 15-minute simulation time step in an attempt to increase the likelihood of quantifying the peak discharge. Modeling at a shorter time steps has been
identified as a way to improve flood prediction in small, fast responding watersheds (NRC, 2006).

Precipitation measurements obtained through in-situ methods may sometimes miss certain small-scale events due to their spatial distribution. The density of the network of in-situ measurements has been studied in the context of being the most important factor in subbasin precipitation uncertainty (Bradley et al., 2002). Bradley et al. (2002) also analyzed the effect of basin size, and gauge measurement error on the uncertainty of subbasin-wide rainfall averages. They calculated the uncertainty in precipitation averages based on the density of the network (Figure 1). They also showed that the root mean squared error (RMSE) was slightly higher for randomly-placed gauge networks (similar to the observations from the Ames Alert network, which will be shown in this study) when compared to networks of the same density on a uniform grid spacing. Krajewski et al. (1991) also studied rainfall input uncertainties but by using synthetic events. They found that the largest source of uncertainty was the temporal resolution of the input data, followed by the spatial resolution with varying degrees of error between events.
Figure 1. RMSE for (a) storm total precipitation and (b) hourly precipitation as a function of gauge density, based on a study of the Catskill region by Bradley et al (2002).

In contrast to precipitation gauge networks, NEXRAD data is measured remotely and it has a much higher spatial resolution. In the context of the Bradley et al. (2002) study, NEXRAD data should also have slightly reduced uncertainty due to observations being on an
organized grid. This paper presents a method to bias adjust NEXRAD precipitation estimates from the University of Iowa’s Hydro-NEXRAD system and input as a spatial precipitation estimate to hydrologic models. Since NEXRAD is only a remote sensing tool, sometimes significant estimation biases have been observed. More on precipitation measurement and estimation errors will be discussed later.

For basins without a fairly dense precipitation gauge network, NEXRAD precipitation estimates might be a good option for operational flash flood forecasting due to the consistent spatial and temporal resolution of the data. NEXRAD precipitation estimates are subject to errors and biases, as mentioned, and in most cases need to be adjusted before use in a streamflow model, as large errors can be compounded and increase as they are converted to modeled streamflow (Neary et al., 2004; Hossain et al., 2004). Although past research has shown that errors can exist due to poor spatial and temporal resolution, quantifying estimations of bias in each subbasin provides a simple way to make estimations more representative of actual measured precipitation at the surface. Both Neary et al. (2004) and Hossain et al. (2004) concluded that once corrections were applied to NEXRAD precipitation estimates, uncertainty in hydrological model simulations would be roughly the same as that of gauge-observed precipitation averaged over studied watersheds.

The HEC-HMS was calibrated and evaluated for historical streamflow simulations in two watersheds in central Iowa. Precipitation time series from the City of Ames’ flash flood alert network and data from the University of Iowa’s experimental radar-based precipitation product, Hydro-NEXRAD (Krajewski and Kruger, 2007), were used as input to the HEC-HMS. In order to increase the relevance to operational forecasting, data sources in the
verification periods will only be used if it will have been available at forecast time, which was generally considered to be the point at which event precipitation ended.

This thesis is organized as follows:

- In Section 2.0, the study area, the data requirements of the HEC-HMS model, and the major model components are discussed.
- In Section 3.0, the GIS analysis used to create the simple bias correction scheme for the NEXRAD precipitation estimates are discussed.
- In Section 4.0, the stages required to obtain an adequate calibration of the HEC-HMS using observed precipitation as the input are discussed.
- In Section 5.0, testing of the remotely-sensed NEXRAD precipitation estimates is discussed.
- In Section 6.0, the results and implications on operational flash flood forecasting are discussed.
2 Methodology

2.1 Study site

The study area consists of two watershed located near Ames, IA (Figure 2). The Squaw Creek watershed is defined by its outlet at the Lincoln Way USGS gauge and has a drainage area of 204 mi$^2$ (Table 1). The Skunk River watershed is defined by its outlet at the Riverside Drive USGS gauge and has a drainage area of 315 mi$^2$. Stream slopes of the basins are 1% or less. The study area is located within the Des Moines Lobe of the Wisconsin glaciations which made their final retreat from central Iowa 12,000 to 14,000 years before present (http://www.igsb.uiowa.edu/Browse/landform.htm). Soils in the area are generally poorly drained and composed of glacial till and organic matter. The terrain is generally flat with minimal post-glacial erosion. Tile drainage is frequently used in the area to maintain a lower water table for row crop production. Yearly precipitation averages from official climate-reporting stations within the two watersheds range from 32.45 inches per year to 35.02 inches per year (MRCC, 2009).

Table 1. Information about the study watersheds.

<table>
<thead>
<tr>
<th>USGS Gage #</th>
<th>South Skunk River near Ames, IA (Riverside Drive)</th>
<th>Squaw Creek at Ames, IA (Lincoln Way)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drainage area</td>
<td>5470000</td>
<td>5470500</td>
</tr>
<tr>
<td>square miles</td>
<td>315</td>
<td>204</td>
</tr>
<tr>
<td>Gage datum</td>
<td>888.6</td>
<td>881.0</td>
</tr>
</tbody>
</table>
Figure 2. Map of the study area. The subbasins highlighted in blue are in the Squaw Creek watershed. The subbasins highlighted in green are in the Skunk River watershed. Precipitation gauges are marked with red dots.

2.2 Data

Discharge data is required for model calibration and verification. Discharge data from points within the study basins were retrieved from four stream gauges operated by the City of Ames for the Ames ALERT Network and from two stream gauges operated by the United States Geological Survey (USGS). Additional required data are precipitation to drive the model simulation, and soil moisture for model initialization. Data used in this study spanned calendar years 2006-2008 and was collected from several different sources.

Precipitation data was retrieved from nine gauges which are part of the Ames Alert Network and from the University of Iowa Hydro-NEXRAD derived radar precipitation estimates. Hydro-NEXRAD is a system developed at the University of Iowa that allows a
user to request NEXRAD precipitation estimates based on user-selected parameters and algorithms. The user can alter the relationship between radar energy return and rain rate (Z-R relationship) that is used in the calculation and can also choose between a set altitude above the radar site or a set standard elevation angle. In this study, the constant altitude plan position indicator (CAPPI) interpolation based on precipitation radar reflectance, or decibels of Z (dBZ), at multiple elevation angles was used in an attempt to create the dBZ values nearest to the user-specified height (Krajewski, et al. 2008). CAPPI is described further in Section 3.1. The minimum DBZ value for measureable precipitation can also be set, along with the DBZ cap, where all higher values are reset to the cap value. Additional settings such as range correction, advection correction, and anomalous propagation reduction can be used to try and improve the NEXRAD estimates. Precipitation data processing and correction are discussed in Sections 3.4.

Soil moisture estimates were retrieved from the in-situ National Resources Conservation Service (NRCS) Soil Climate Analysis Network (SCAN) sensor near Ames (http://mesonet.agron.iastate.edu/scan/) and from the Water Erosion Prediction Project (WEPP) model output (http://wepp.mesonet.agron.iastate.edu/). The WEPP model is a continuous simulation model that uses gridded precipitation as an input and provides soil erosion and soil moisture estimates as an output. The WEPP model was created by the National Soil Erosion Research Laboratory (NSERL) for use by the USDA and other interested government agencies involved in soil erosion and environmental planning (http://topsoil.nserl.purdue.edu/nserlweb/weppmain/docs/readme.htm). The WEPP model parameters are measured characteristics of soil properties along a desired hill slope. The
Iowa State University Department of Agronomy runs the model daily, for several hill slopes in each township across the entire state of Iowa. The WEPP model uses the Green & Ampt infiltration equation to model runoff and account for changes in soil moisture. The final states of the soil moisture and soil erosion components of the WEPP model are available in geographic information systems (GIS) shapefile format each day just after noon. The SCAN data is available every hour with the most recently updated data only a few hours behind real-time.

We chose the WEPP model for this study because of its availability in GIS shapefile format in near real-time over the internet, and because many faculty members in our department were quite familiar with the model and how it was developed. The Ames SCAN site was also chosen because it is the nearest real-time, in-situ measurement available to the study basins. Data from both sources were used because each source had relative benefits. The SCAN site was directly measured, and the WEPP output had spatial variability because it is run for every township in Iowa.

The soil moisture values obtained from the WEPP GIS shapefile output were adjusted based on the last-available SCAN site value before the onset of precipitation in each examined event. The difference between the SCAN site average of the previous 24 hours and the soil moisture value for the 0-20cm soil layer in the WEPP model grid representing the associated township was calculated. This difference was then applied to the WEPP output in every township. Then, the soil porosity was divided by the adjusted WEPP soil moisture values to compute a moisture deficit value that is required by the Green & Ampt method discussed in the next section. A soil porosity value of 41% was used for this study,
as that was the soil moisture content measured by the SCAN site during saturated conditions. The moisture deficit values in each township were then averaged spatially by subbasin extent and used to initialize the watershed simulation.

2.3 Hydrologic Model

The HEC-HMS model simulates precipitation-runoff processes at the watershed scale. Model input is precipitation, and output is streamflow discharge. The HEC-HMS is composed of several different modeling components that make up the entire watershed model (Figure 3), including: (a) a meteorological model that handles precipitation inputs, (b) a loss method (infiltration model) that calculates runoff, and (c) a transform function that routes runoff to subbasin outlets, and (d) a routing function that accumulates modeled flow from each of the distributed subbasins, creating a streamflow hydrograph. There are several different methods available for each modeling component. The setup of the HEC-HMS for the Skunk and Squaw watersheds is shown in Figure 4.
Figure 3. Flow chart of the various components of the HEC-HMS model showing the progression of precipitation input to streamflow output.
2.3.1 Meteorological model

The Thiessen polygon precipitation distribution method is used for the meteorological model when the gauge-based ALERT precipitation observations are used as the model input. Gauge weights for the polygon of each precipitation gauge were calculated through GIS.
methods. The specified hyetograph (precipitation time-series) meteorological model is used when NEXRAD precipitation estimates are the model input. The radar estimated precipitation data is averaged over each subbasin by an external script. A separate precipitation time series for each basin is produced, and then used as the specified hyetograph for model input.

2.3.2 Infiltration model

The Green & Ampt (GA) infiltration equation was chosen for the infiltration model due to its relative simplicity and low number of parameters that require calibration. The GA infiltration model is based on Darcy’s Equation for flow in porous media (Harris & Hossain, 2008). The GA model has also been shown to simulate runoff as well as or better than other commonly-used infiltration methods, such as the empirically-based SCS Curve Number method (Wilcox et al., 1990). The GA requires a specified initial abstraction, percent impervious surface, wetting front suction head, initial soil moisture deficit, and hydraulic conductivity. The model is considered physically-based because these parameters can be either directly measured by taking soil samples or can be estimated based on other soil properties (Wilcox et al., 1990).

The GA initial abstraction is a threshold of precipitation that must be met before water begins to interact with the soil such that infiltration or runoff will occur. In this study, the abstraction was calculated to be the canopy storage plus the soil surface depression storage. Llorens (2000) gives estimated values of canopy storage based on plant species. Various species similar in leaf size to those found in central Iowa were used. The values for
three different tree species - Nyssa sylvatica, Aleurites moluccana, and Argyrodendron peralatum – were averaged. Based on this average value, the precipitation retention by an area of 100% canopy cover was assumed to be 4.13mm, or 0.16in. A GIS raster dataset was obtained from the Iowa State University (ISU) Geographic Map Server that showed estimates of percent canopy cover over the subbasins of the Riverside and Lincoln Way watersheds. The percent canopy cover was multiplied by the precipitation retention value, and then was spatially averaged over each subbasin. Guzha (2004) stated that the maximum soil surface retention value for tillage methods common to Iowa was 1.18in when no rainfall since tilling has occurred. Soil surface retention represents the precipitation that is retained in roughness of the soil surface. Although this value should decrease as the soil surface is smoothed from cumulative precipitation post-tilling, we assumed this maximum retention value to be constant over the bare soil or crop regions for model simplicity. The SCS Curve Number depression storage equation approximates the depth of depression storage for a rainfall event as:

\[
Depression\ Storage = 0.2 \times S_{max},
\]

where \(S_{max}\) is the maximum soil surface retention value. Based on Equation 1, the surface depression storage for soils for the entire region was assumed to be 0.24in. Once the abstraction values from canopy cover and soil surface retention were summed (Figure 5), the values were averaged by subbasin and used for the GA initial abstraction value. The GIS-derived values for initial abstraction that were used with the HEC-HMS are listed in Table 2.
Hydraulic conductivity and wetting front suction head parameters for the subbasins were estimated based on the WEPP model spatial averages, published table values, and model calibration, and is discussed in Section 4.0.

Figure 5. GIS-derived initial abstraction values for the Squaw Creek watershed (west branch) and the Skunk River watershed (east branch).
2.3.3 Transform (runoff routing) model

The SCS Unit Hydrograph method was used for the transform function. The unit hydrograph is an average streamflow response derived from empirical data of numerous past events, and is a function of drainage area, subbasin lag time, and runoff precipitation. Runoff precipitation calculated from the infiltration model is fed to this unit hydrograph, which is in units of ft³/second/inch-runoff. The lag time parameter is defined as the time between hydrograph peak and event rainfall “center of mass” (NOHRSC, 2005). Drainage area was obtained through GIS analysis and the value for the lag time parameter was identified through calibration.
2.3.4 Stream Routing (Muskingum)

The Muskingum routing method was used for modeling the open channel reaches. The stream routing method simulates attenuation of the flash flood peak as flow is accumulated over each subbasin in the model. Two parameters are required for the Muskingum routing routine. The Muskingum X parameter was set at the default value of 0.2 and the Muskingum K parameter was determined through calibration. The X parameter works to simulate attenuation of streamflow volume, and the K parameter simulates a delay in streamflow (in hours) as it moves through the channel. Through the model development process it was observed that a good approximation of the Muskingum K parameter in our watersheds is 1 hour per stream-mile. More study is required to confirm the applicability and accuracy of this approximation.
3 NEXRAD Precipitation Analysis

Precipitation measurements obtained through in-situ methods may sometimes miss spatially small-scale events leading to underestimation of the basin-wide precipitation. Conversely, rain gauges can lead to over-estimation of precipitation if a localized event happens to pass over the observation point but impacts only a small portion of the basin. Underestimation may also occur in windy conditions, such as those experienced under convective storms. Radar-based precipitation products have the potential to overcome the uncertainty in spatial precipitation estimates introduced by point-scale measurements. However, because NEXRAD is a remote sensing tool for measuring precipitation rates in the atmosphere, significant biases in estimated ground level precipitation have sometimes been observed. In this section, the NEXRAD precipitation estimates from the University of Iowa’s Hydro-NEXRAD are analyzed and a bias correction scheme is developed in order to prepare a radar-based precipitation time series for input to the HEC-HMS. Analysis of the magnitude and spatial extent of the data biases was done using ESRI’s ArcGIS Spatial Analyst tools. Specifically, the interpolate-to-raster tools are used to compare the observed point measurements to the gridded, remote-sensed data.

Choosing a NEXRAD algorithm to use in the calculation of precipitation estimates is not a clear-cut task. Different algorithms are chosen for different purposes based on things such as distance from the radar, topography of the basin and vicinity, and computational constraints. Fulton et al. (1998) discussed use of the NWS hybrid scan that is a combination of tilts from the radar’s volume scan, where the lowest unblocked tilt is used at every azimuth angle, provided that it is not significantly contaminated by ground clutter. Fulton et
al. (1998) also discussed CAPPI interpolations used for radar precipitation estimates and a potential source of uncertainty, specifically that temperature and moisture gradients in the atmosphere can bend the radar beam downward or upward and cause ground targets to be interpreted as rainfall, or cause the expected constant altitude scan to not actually be constant in altitude. At this time, there is no simple way to correct for these phenomena, nor is there a simple way to know the extent to which this is happening as it can change through both azimuth direction and time.

3.1 NEXRAD Precipitation Estimation Algorithms

The files obtained from the University of Iowa’s Hydro-NEXRAD system are provided on the Hydrologic Research Analysis Project (HRAP) grid, which can have variable spacing depending on the latitude. In central Iowa, each grid cell averages about 4.3km by 4.3km. The files are in the ArcASCII format, which can be read by ArcGIS as a GIS raster file. The Pseudo-NWS PPS, 1.3km CAPPI height, and HiFi NEXRAD precipitation estimation algorithms, as described by (Krajewski, et al., 2008), were tested in this study:

- The Pseudo-NWS Precipitation Processing System (NWS PPS) algorithm is meant to closely resemble the precipitation estimates obtained by local WFO offices and uses the lowest possible NEXRAD scan angle at each azimuth (which is only the 0.5 degree radar scan since there are no terrain obstructions in central Iowa), an 18dbz rain threshold, and a 53dbz hail cap. It should also be noted that the PPS in use by the National Weather Service is more complicated than the Pseudo-NWS PPS algorithm available through Hydro-NEXRAD. The NWS PPS system contains over
40 adaptable parameters (Fulton, Breidenbach, Seo, & Miller, 1998) as compared to the half dozen or so available in the Hydro-NEXRAD.

- The constant altitude plan position indicator (CAPPI) algorithm attempts to obtain radar returns from a near-constant altitude which can help normalize range effects from ground clutter and bright-banding, and uses a rain threshold of 10dbz along with a hail cap of 53dbz. A constant altitude of 1.3km above radar level was selected because the lowest average height of the radar beam above the basins at the farthest point from the radar site is near 1.3km. Once data from multiple radar elevation angles is obtained (Figure 6), a kernel smoothing algorithm is applied to reduce discontinuities as the data changes from tilt to tilt.

- The HiFi algorithm also uses a constant altitude, which is set at 1.5km above radar level by the algorithm. The rain threshold and hail cap are also the same with HiFi as with CAPPI, but corrections are added for ground clutter, distance from radar, and storm motions.
3.2 Precipitation Observations

The precipitation gauges in the Ames ALERT Network are the tipping-bucket style, and have a measurement resolution of 0.01 inches. Spacing of the gauges is non-uniform, and distances between gages range from about 4 miles to just over 20 miles (Figure 7). The maximum distance would have been lower if the precipitation gauge at Ellsworth (in the very middle of the headwater subbasin of the Skunk River watershed, between Blairsburg and E18Skunk) was in operation. For most of the time periods used in this study, this gauge was offline and was therefore not used in any of the analysis presented.
3.3 Calculating NEXRAD Precipitation Estimate Biases

Although not much work on NEXRAD precipitation estimates has been done specifically using GIS and observed gauge interpolations, there has been significant work done to attempt to quantify errors in both estimated and observed rainfall (Anagnostou and Krajewski, 1999; Bradley et al., 2002; Hossain et al., 2004; Hunter, 2008; Krajewski et al. 1991). Precipitation gauges usually serve as the “true” observed value, although there can be significant measurement errors in gage observation of up to 5-40% during strong thunderstorms (Hunter, 2006), which are typically localized events. Many flash flooding events include a significant portion of rainfall input from convective thunderstorms and, as a
result, gauge observations are more likely to under-catch actual precipitation in these situations. Uncertainty errors in subbasin-wide precipitation estimates are also tied to spatial and temporal resolution of the data, as discussed earlier. The RMSE observed at study basins in the Catskill region versus the density of rain gauge networks used to calculate the average precipitation (Figure 1) was studied by Bradley et al. (2002). Based on their results, a rain gauge density of 0.0089 gauges/km$^2$ in the LincolnWay watershed and 0.0049 gauges/km$^2$ (0.0061 gauges/km$^2$ if Ellsworth were online) in the Riverside watershed would yield a RMSE in hourly sub-basin precipitation averages of 20% and 28% (25%), respectively. It should be noted that the Catskill region is significantly more hilly than Central Iowa, with differing soil types, so there is uncertainty when applying these error estimates to our study area. A study was also conducted by Anagnostou and Krajewski (1999) with the purpose of looking into variance of radar-rainfall estimation error with a grid spacing of 4km by 4km, which is similar in size to the HRAP grid over central Iowa. They found that rain gauge precipitation observations can deviate significantly from the true mean-areal rainfall over a basin, many times with high error variability over short distances. They showed in their case studies that the standard deviation of hourly error was about 60% of the mean error at radar ranges similar to that of the southern subbasins in the Skunk and Squaw watersheds. In addition, up to 60% of the observed differences between NEXRAD estimates and observations were due to uncertainty in the measured values at the gauges. The NEXRAD estimates will be compared to the interpolated gauge values without any adjustments for these potential errors and uncertainties, so this should be a caveat for the results in this portion of the study. Despite these potential errors, the precipitation gauges are still widely considered to be most accurate.
Yatheendradas et al. (2008) reported that errors in NEXRAD estimation can be amplified in watershed models. As the NEXRAD beam gets farther away from its source, the width and height of the beam expand, causing a much larger area to be scanned at a given azimuth direction. Larger radar beam widths reduce sampled variability of the actual precipitation by the radar and these errors can be magnified in watershed models due to their non-linearity. Yatheendradas et al. (2008) also suggested that high-resolution networks of precipitation gauges in conjunction with these radar estimates are needed to provide adequate representations of the “real” precipitation that is falling over the modeled basin. Parameters such as the Z-R relationship used to calculate the rainfall rate have been shown to vary widely between different storms in the same areas of the country. Because there is no way to know the right way to change these parameters on the fly during a flood forecasting situation, the standard Z-R relationship of the NWS PPS was used throughout this study.

Krajewski and Smith (2002) found that event-based radar rainfall estimates could be improved by a simple scalar value applied to the estimates. The scalar adjustment could be calculated based on a collection of available precipitation gauges for “ground truth” in the basin and their comparative magnitude of precipitation against that of the NEXRAD estimates in the same area. This is the approach taken to bias correct NEXRAD precipitation estimates prior to using them as input to the HEC-HMS. The best approach for scalar adjustment in this study appears to be the calculation of biases in the NEXRAD estimates for each subbasin. These biases could be removed from the data set as the ArcASCII files are pre-processed for hydrological modeling. An attempt to quantify potential errors in the different Hydro-NEXRAD algorithms mentioned above was conducted by Kyle Johnson
during a 2008 summer research project at ISU. The scope of his project was limited to the E18Skunk basin which is in the headwaters portion of the study area, and located furthest from the radar site in Des Moines, IA. Preliminary results from this analysis showed that the CAPPI algorithm performed the best in comparison to algorithms similar to the HiFi method. The “HiFi” algorithm was also shown to have the most event-to-event variability in error of all the algorithms used during April and May. The present study will look for possible consistency or conflict with these results when the analysis is expanding to a larger study area.

3.4 NEXRAD Precipitation Estimate Data Processing

A GIS dataset of active precipitation gauges in the basins was imported into ESRI’s ArcMap as a GIS layer. Fields for spring 2007 and spring 2008 precipitation were added to the layer’s attribute table. In the spring 2007 field, the total April 1\textsuperscript{st} to June 30\textsuperscript{th} precipitation at each gauge was input. In the spring 2008 field, the total April 1\textsuperscript{st} to May 9\textsuperscript{th} precipitation at each gauge was input. On May 9\textsuperscript{th}, 2008, NOAA changed the NEXRAD format to super-resolution. Because the Hydro-NEXRAD system has not yet been modified to handle this new data format, no data past May 2008 were available.

NEXRAD precipitation estimates from Hydro-NEXRAD were analyzed using Matlab. The ArcASCII files were imported to Matlab on a 15-minute time step. The precipitation value for each time step was added together for each HRAP grid cell. The output of the program was a new ArcASCII-formatted file of the precipitation totals for each grid cell. A file was created for each NEXRAD precipitation algorithm. This file was imported into ArcMap with the projection defined as HRAP. The HRAP projection uses a
different datum than most other standard projections and no transformations are available. Because of this, the file was then projected to North American Lambert Conformal Conic because this is a format that the observed precipitation grids could be converted to without the need of a geographic transformation. Once projected, the radar estimation rasters were saved in the GRID format. The raster calculator function was used to convert the values to inches, since the standard unit for Hydro-NEXRAD is millimeters.

Using the tension spline interpolation algorithm in ArcGIS’s spatial analyst functionality, a grid of observed precipitation values in inches was created on the same HRAP projection as the radar estimated precipitation rasters. The raster calculator was then used to subtract the observed values from the estimated values at each grid cell, and the difference was then divided by the observed values as shown with:

\[
\text{Bias} = \frac{(\text{NEXRAD Estimate}) - (\text{Interpolated Observation})}{(\text{Interpolated Observation})},
\]

where \textit{NEXRAD Estimate} is the estimated precipitation value for the specified algorithm and \textit{Interpolated Observation} is the estimated value based on the tension spline interpolation scheme. ArcGIS’ spatial analyst function executed Equation 2 at each grid cell. This process was repeated for each heavy precipitation event and both springtime periods. The full springtime periods were used to calculate this bias and grid values were averaged over each subbasin. The individual precipitation events were used to analyze event-to-event variability. A bias correction factor for each subbasin was calculated from this subbasin bias value, and used as a scalar adjustment to the precipitation estimates. Quantifying estimations of bias in each subbasin provides a way to make simple adjustments to the NEXRAD data in
an attempt to make it more representative of actual measured precipitation at the surface, and accounts for some degree of spatial dependency in the bias estimates.

3.5 GIS NEXRAD Bias Results

The radar estimated precipitation bias as compared to the rain gages for the April 1st to June 30th, 2007 time period varied by subbasin and precipitation estimation algorithm (Table 3). The computed bias in the Pseudo-NWS PPS algorithm ranged from -1% in the LincolnWay basin to +55% in the E18Skunk basin (Figure 8, Table 3). The bias in precipitation estimates based on the CAPPI algorithm ranged from +15% in the LincolnWay basin to +58% in the E18Skunk basin (Figure 9, Table 3). Finally, the bias in precipitation estimates from the HiFi algorithm ranged from -4% in the LincolnWay basin to +56% in the E18Squaw basin (Figure 10, Table 3). With all methods, the general trend in bias is a positive increase as distance from the radar increases (towards the north).

Table 3. Percent error of each precipitation estimation algorithm from April 1st to June 20th, 2007, when averaged over each subbasin.

<table>
<thead>
<tr>
<th>Subbasin</th>
<th>E18Skunk</th>
<th>E18Squaw</th>
<th>McFarland</th>
<th>CSR</th>
<th>LincolnWay</th>
</tr>
</thead>
<tbody>
<tr>
<td>NWS PPS</td>
<td>+55%</td>
<td>+40%</td>
<td>+23%</td>
<td>+13%</td>
<td>-1%</td>
</tr>
<tr>
<td>CAPPI</td>
<td>+58%</td>
<td>+42%</td>
<td>+26%</td>
<td>+24%</td>
<td>+15%</td>
</tr>
<tr>
<td>HiFi</td>
<td>+49%</td>
<td>+56%</td>
<td>+26%</td>
<td>+37%</td>
<td>-4%</td>
</tr>
<tr>
<td>Average</td>
<td>+54%</td>
<td>+46%</td>
<td>+25%</td>
<td>+25%</td>
<td>+3%</td>
</tr>
</tbody>
</table>
Figure 8. Basin-averaged NEXRAD precipitation estimate bias (percent of observed) for spring 2007 using the NWS PPS algorithm.
Figure 9. Basin-averaged NEXRAD precipitation estimate bias (percent of observed) for spring 2007 using the CAPPI 1.3km AGL algorithm.

Figure 10. Basin-averaged NEXRAD precipitation estimate bias (percent of observed) for spring 2007 using the HiFi algorithm.
Similar to results from 2007, the GIS analysis for 2008 showed differences between the observations and NEXRAD precipitation estimate algorithms that varied by subbasin and precipitation estimation algorithm (Table 4). For the April 1st to May 9th, 2008, data using the NWS PPS algorithm the percent difference of estimates from observed ranged from -3% in the LincolnWay basin to +97% in the E18Skunk basin (Table 4). Using the CAPPI algorithm, the percent difference of estimates from observed ranged from +11% in the LincolnWay basin to +83% in the E18Skunk basin (Table 4). Using the HiFi algorithm, the percent difference ranged from -26% in the LincolnWay basin to +40% in the E18Skunk basin. With all methods, the general trend in bias is again a positive increase as distance from the radar increases (towards the north). It should be noted that the data availability for spring 2008 was much less than that of 2007, and therefore the data may not be representative enough to fully compare with the data from the previous year.

Table 4. NEXRAD precipitation estimation algorithms as a percent of observations from April 1st to May 9th, 2008, when averaged over each subbasin.

<table>
<thead>
<tr>
<th>Subbasin</th>
<th>E18Skunk</th>
<th>E18Squaw</th>
<th>McFarland</th>
<th>CSR</th>
<th>LincolnWay</th>
</tr>
</thead>
<tbody>
<tr>
<td>NWS PPS</td>
<td>+97%</td>
<td>+48%</td>
<td>+35%</td>
<td>+26%</td>
<td>-3%</td>
</tr>
<tr>
<td>CAPPI</td>
<td>+83%</td>
<td>+39%</td>
<td>+32%</td>
<td>+29%</td>
<td>+11%</td>
</tr>
<tr>
<td>HiFi</td>
<td>+40%</td>
<td>+17%</td>
<td>+3%</td>
<td>-1%</td>
<td>-26%</td>
</tr>
<tr>
<td>Average</td>
<td>+73%</td>
<td>+35%</td>
<td>+23%</td>
<td>+18%</td>
<td>-6%</td>
</tr>
</tbody>
</table>

Upon examination of the results shown above, some data that was likely causing problems in the calculations were eliminated. Specifically, the bias calculations in the US30 subbasin were potentially inaccurate because no precipitation gauge lies within that subbasin or on either side of it such that an interpolation between two gauges could be made over its extent. The observed precipitation values in the grid cells encompassing the US30 basin
were thus based entirely on rough linear interpolations in data-sparse areas generally outside of the gauged area. The data from the Riverside subbasin was also ignored, as the basin is not large enough to encompass even one full HRAP cell and may not be large enough for a representative average. Because the Riverside subbasin was roughly at the same distance from the nearest radar site (KDMX – Des Moines, IA) as the CSR subbasin, the CSR bias value was applied to the Riverside subbasin. The US30 basin was given the same bias value as the LincolnWay basin, since LincolnWay was the nearest bias value calculated. The spring 2008 period is about half the duration of the springtime 2007 period, therefore, each period’s results were weighted by the time they encompass, so that more weight is given to the spring 2007 results when the bias correction scheme is used.

Based on the April 1\textsuperscript{st} to June 30\textsuperscript{th}, 2007 analysis, the CAPPI algorithm appears to have the most consistent bias between subbasins in the study area, while the HiFi algorithm is the least consistent. Based on visual analysis, the NWS algorithm appears to have the least variability in its error between the three heavy precipitation events and the HiFi algorithm appears to have the most variability between events. The algorithm with the least variability between events will likely be the most useful because there will be more confidence that a computed bias adjustment will maintain applicability across events.

Another important factor to consider when choosing between the precipitation estimation algorithms is the computation time required for creating the files. The CAPPI and NWS PPS algorithms each take about 10 minutes to process data for one full day, while the HiFi algorithm takes a minimum of 30 minutes to complete the same amount of data. These computation times do not include queue times for jobs submitted to the Hydro-NEXRAD
server. Since time can be a major factor when trying to forecast flash floods, the best algorithm for this purpose would likely be either NWS PPI or CAPPI, especially if one of them does better than the HiFi algorithm. The CAPPI or the NWS PPS algorithm both perform similarly, as they have lower variability between individually studied rainfall events and each take about the same time to calculate. Based on information from other studies, and from the work done by Kyle Johnson at ISU, the CAPPI 1.3km AGL algorithm will be used to drive the HEC-HMS streamflow model.


4 HEC-HMS Calibration and Verification

The HEC-HMS model was calibrated to 7 significant rainfall events in Spring 2006 and 2007 using ground-based precipitation and subbasin discharge observations. The model was then verified to 6 storm events from 2008. The discharge data was derived from observed stage using rating curves provided by the city of Ames. Lastly, the bias-adjusted NEXRAD-based precipitation estimates were tested in the calibrated model. Due to the limited data record in the Hydro-NEXRAD system, not all verification events could be tested with NEXRAD precipitation estimates. To assure an adequate sample set for analysis, three events from the calibration period were added to the verification period when evaluating the NEXRAD-driven model.

4.1 Model Calibration and Verification Setup

Initial conditions, such as soil moisture, are crucial to event modeling because they dictate how the watershed response will differ between events with similar rainfall. For operational flood forecasting, an accurate and readily available estimate of soil moisture is needed.

To get an idea of a rough starting point for the soil parameters required by the Green & Ampt Infiltration model, hydraulic conductivity, wetting front suction head, and porosity values from the WEPP model were collected and analyzed. In the WEPP model, the hydraulic conductivity changes by modeling precipitation and tillage effects on the soil profile of the modeled landscape. A daily time series of each of these parameters was obtained by averaging the daily values for hydraulic conductivity, wetting front suction head,
and porosity from 2002 to 2008, the period available from the WEPP. A 15-day moving average was applied to reduce day-to-day variability. To identify initial soil parameter values, the soil parameters coinciding with the first day of a rainfall event were chosen from this plot and used to initialize the model.

Starting from the WEPP derived soil parameters, a number of calibration attempts were conducted in order to refine the model performance to the extent possible. Because the HEC-HMS was being applied in an event-based manner, the model had to be calibrated several times for a number of events. The collective results were analyzed based on reasonableness of the parameter values, and accuracy of the simulations. Automatic calibration techniques were found to produce less than ideal results; specifically, problems with unrealistic parameter values, little improvement in model results, and lack of convergence were encountered. Therefore, manual parameter adjustments were needed. In addition, during preliminary testing with automatic calibration, it was found that events occurring in the middle of summer would frequently fail during automatic calibration or provide values that were significant outliers. This could have occurred because of an issue in the automatic calibration processes in HEC-HMS, or could indicate an inability of model to forecast for events during this time period. Because of these issues, only events that occurred between March 1st and June 30th were included in subsequent model development. The following describes a number of steps taken to attain a satisfactory calibration of the HEC-HMS.
4.2 Stage 1

The automatic calibration option of the HEC-HMS was tried during the first stages of model development. The Univariant Gradient optimization method was used with a tolerance of 0.001 and an iteration cap set at 1000 simulations – the default calibration setup in the HEC-HMS. The objective function was set to peak-weighted root mean squared error. Calibration variables were lag time for the transform function and hydraulic conductivity for the infiltration model. Wetting front suction head and moisture deficit parameters were set to the WEPP-derived daily average values.

Calibrated hydraulic conductivity values in the LincolnWay watershed and also the Riverside watershed were fairly inconsistent between events (Figure 11). Significant deviation from the WEPP-modeled hydraulic conductivity values was also noted. The average calibrated hydraulic conductivity value from both watersheds was calculated, and then the trace of modeled values from the WEPP was adjusted downward until the average value of the daily WEPP-derived values was the same as the calibrated values. This allowed the value of the hydraulic conductivity to be adjusted according to the observed data, but retained the pattern of daily variability used by the WEPP application. Because of the uncertainty noted with the hydraulic conductivity parameter, however, arbitrary uncertainty bounds of 25% and 50% were used in the verification as a means of creating a simple model ensemble and also observing potential model improvements.
During the stage 1 verification period, significant differences between forecast and observations were noted. Average error in timing of peak discharge for the stage 1 verification was 5.3 hours. The average error in magnitude of peak discharge was 1880 ft$^3$/second, or an average of 46% of the observed flow. Only two of the twelve verification forecasts had the observed peak flow within the 50% uncertainty bounds of the modeled peak flow.

Figure 11. Hydraulic conductivity as derived from the WEPP model, as calibrated from rainfall events in 2006 and 2007 using the HEC-HMS automatic calibration, and an averaged value across both watersheds with 25% and 50% uncertainty bounds added.
4.3 Stage 2

In stage 2, a sensitivity analysis was conducted to determine which parameters had the most uncertainty in the modeling process and which should be the focus of additional refinement to improve the model results from stage 1. The wetting front suction head, moisture deficit, and hydraulic conductivity of the Green & Ampt infiltration model, and the lag time of the transform function were included in the analysis. The streamflow peak of twelve events was calculated after a reduction of 25% in each variable, and also an increase of 25% of each variable. The percent sensitivity is the difference in estimation of streamflow from the 25% increase and the 25% decrease, as a percentage of the observed peak flow value of the event. Modeled streamflow was found to be relatively insensitive to changes in the wetting front suction head variable and the lag time when compared to changes of the same percentage in the hydraulic conductivity variable. The hydraulic conductivity and the soil moisture deficit were the most sensitive parameters, with the hydraulic conductivity having the highest sensitivity (Figure 12).

Because adjustments to the wetting front suction head parameter had very little impact on simulated streamflow, it was set to the average WEPP-derived value in both watersheds of 1.2 inches to simplify the model application. The model was simplified further by setting the hydraulic conductivity value to a constant 0.09 inches/hour, which was the average calibrated value from stage 1. The calibrated hydraulic conductivity values from stage 1 did not follow the values predicted by the WEPP or show any consistent change with time, therefore altering the hydraulic conductivity with time was decided to be an unnecessary complication with no apparent added value.
Figure 12. Sensitivity of the hydraulic conductivity and the moisture deficit variables used in the Green & Ampt infiltration model of HEC-HMS. The y-axis represents individual precipitation events represented by their peak observed streamflow value. The x-axis represents the difference in streamflow peak observed between increasing the parameter by 25% and decreasing the parameter by 25%, as a function of the observed peak streamflow.

During stage 1, a correlation between the magnitude of the transform function lag time and the number of days since previous rainfall was observed. To test the strength of the correlation between these two variables, the number of days between the previous 0.25 inch rainfall event (a reasonable lower threshold) and the model start time was counted and then plotted against the ratio of calibrated lag time to the average lag time for all subbasins in each watershed. A linear trend line was fit to the data from both the LincolnWay watershed and the Riverside watershed. The $R^2$ correlation between days-since-rainfall and the lag time multiplier was 0.90 for the LincolnWay watershed and 0.96 for the Riverside watershed (Figure 13). The equation for the best-fit linear trend line was the same for both watersheds. When the data from each watershed were plotted together, the $R^2$ correlation remained as
high as for the Riverside watershed, at 0.96, and the equation remained the same (Figure 13). Although, in the standard application of the SCS unit hydrograph the lag time parameter is meant to be a function of watershed slope, land use, and longest flow path, and is considered to be constant in time, results strongly indicate that the lag time parameter is partly related to antecedent precipitation. Therefore, some adjustment may be necessary to attain optimal model results.

The change of the lag time multiplier based on previous precipitation and the high sensitivity of the hydraulic conductivity parameter were taken into account in stage 2 of model development which entailed manual adjustment of hydraulic conductivity and
application of the lag time multiplier equation shown in Figure 13. After adding these steps to the process, we verified the model again.

A slight improvement in the modeling performance was noted once the lag time multiplier was added and the wetting front suction head parameter was set to a constant value. Average error in timing of peak discharge for the verification was 4.0 hours. The average error in magnitude of peak discharge was 1773 ft$^3$/second, or an average of 40% of the observed flow, yielding a 107 ft$^3$/second and 6% improvement over Stage 1 flow results, respectively. Only one of the twelve events were within the hydraulic conductivity 50% uncertainty bounds, while two of the twelve were within 500 ft$^3$/second of the bounds and nine of the twelve peak flows were outside of the uncertainty bounds, but within 500 ft$^3$/second.

4.4 Stage 3

It was noted from the previous calibration that hydraulic conductivity values appeared to be consistently too low, which would yield frequent, and sometimes significant, model overestimates. Because the calibrated hydraulic conductivity values were unsatisfactory, we looked for accepted hydraulic conductivity values for soils similar to those in the study region. Soils in the study area are usually classified as “loam” or sometimes as “silt loam.” The hydraulic conductivity values for the Green and Ampt method suggested by Rawls et al. (1983) for loam and silt loam (Table 5) are consistent with modeled values derived from the WEPP. Therefore, a hydraulic conductivity value of 0.15 inches/hour was chosen for future verifications because that was the most common daily value from the WEPP output. The only time when this parameter deviated significantly from 0.15 inches/hour in the WEPP
during the calibration period was while tilling of agricultural lands was taking place. Tilling would generally be unpredictable to someone using this model operationally, so the impact of tilling was ignored for this study.

Table 5. Soil property values by soil type for use with the Green & Ampt infiltration equation as derived from published values in Rawls et al. (1983)

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>Hydraulic Conductivity (inches/hour)</th>
<th>Wetting Front Suction Head (inches)</th>
<th>Effective Porosity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loam</td>
<td>0.13</td>
<td>3.5</td>
<td>43%</td>
</tr>
<tr>
<td>Silt Loam</td>
<td>0.26</td>
<td>6.6</td>
<td>49%</td>
</tr>
</tbody>
</table>

An improvement in the modeling performance was noted once the adjusted hydraulic conductivity value was used. The average error in timing of peak discharge for the verification was 3.0 hours. The average error in magnitude of peak discharge was 1414 ft³/second, or an average of 25% of the observed flow, yielding a 359 ft³/second and 15% improvement over Stage 2 flow results, respectively. Five of the twelve events were within the hydraulic conductivity 50% uncertainty bounds, while three of the twelve were within 500 ft³/second of the bounds and four of the twelve peak flows were outside of the uncertainty bounds. On average, the modeled event flow for all verification events was very close to the observations (Figure 14; Figure 15), particularly at the Riverside gauge. All simulations for individual events from the final calibration (Stage 3) are provided in Appendix A, Section A.1.
Figure 14. Average event flow for all verification events of Stage 3, for both the Riverside (top) and LincolnWay (bottom) watersheds. The solid blue line represents the average event flow from the HEC-HMS model output and the solid black line represents the average event flow from observations. The shaded areas show the standard deviation at each 15-minute interval for the modeled streamflow (blue) and observed streamflow (gray).
Figure 15. Average error in event flow for all verification events of Stage 3, for the Riverside (top) and LincolnWay (bottom) watersheds. The blue line represents the modeled streamflow error compared to observed streamflow, in ft$^3$/second. The red line represents the modeled streamflow error as a percentage of observed streamflow, at each 15-minute time step.
5 NEXRAD Precipitation Estimates as HEC-HMS Input

Once the calibration was complete and minimal model improvements were expected through additional testing, the NEXRAD precipitation estimates were tested as input to the HEC-HMS. A Matlab script was written to process the files from the Hydro NEXRAD system. All of the files in a specified folder were opened, and the values of a given HRAP grid cell were summed for each time step of interest (one file represents one time step). Once the storm total rainfall is calculated on a gridded basis, the values are then averaged over each subbasin in the LincolnWay and Riverside watersheds. The final output from the Matlab script is a time series of basin-averaged precipitation that can be entered into the HEC-HMS. That time series of uncorrected NEXRAD precipitation estimates was tested as input to the model and hydrographs with the 25% and 50% uncertainty bounds for hydraulic conductivity were produced, as was done in Section 4. Results for LincolnWay and Riverside gages are shown in Figure 16.

Because of the switch to super-resolution NEXRAD data in May of 2008 and the inability of the Hydro-NEXRAD system to process the new file format, four dates that were included in the verification period during model development (total of 8 verifications) could not be used. Therefore, four dates from the original calibration period were chosen to include in the evaluation of the NEXRAD data.

An improvement in the model’s ability to simulate the shape of the observed flow was noted when the model was driven with NEXRAD data, but error increased in the forecasts of the timing and magnitude of peak. The average error in timing of peak discharge for the verification was 5.9 hours. The average error in magnitude of peak
discharge was 1791 ft$^3$/second, or an average of 65% of the observed flow. Four of the ten events were within the hydraulic conductivity uncertainty bounds, while six of the ten were outside of the bounds. All simulation for individual events using the uncorrected Hydro-NEXRAD data are provided in Appendix A, Section A.2.

Figure 16. Modeled streamflow hydrographs for the LincolnWay and Riverside streamflow gauges during the April 24-28, 2007, event. Hydraulic conductivity (HC) uncertainty bounds are shown for the HEC-HMS model driven by uncorrected NEXRAD precipitation estimates. Observed streamflow (OBS) is shown in black.
5.1 Applying Scalar Bias-correction to NEXRAD Precipitation Estimates

The NEXRAD bias values determined through GIS methods were next applied to the Hydro NEXRAD precipitation estimates. The Matlab code that processed the remotely-sensed precipitation estimates was modified to include a bias parameter for each subbasin in the LincolnWay and Riverside watersheds. The bias was factored out of the time series at every time step as shown by:

\[ \text{Correction Factor} = \frac{1.0}{\text{Bias}}, \tag{3} \]

where \( \text{Bias} \) is the value determined from Equation 2 and \( \text{Correction Factor} \) is the value multiplied by the estimated precipitation at each time step. The time series of bias-corrected NEXRAD precipitation estimates were then used to drive the HEC-HMS model (Figure 17).
Figure 17. Modeled streamflow hydrographs for the LincolnWay and Riverside streamflow gauges during the April 24-28, 2007, event. Hydraulic conductivity (HC) uncertainty bounds are shown for the HEC-HMS model driven by bias-corrected NEXRAD precipitation estimates. Observed streamflow (OBS) is shown in black.

Once the simple bias correction scheme was implemented, model performance improved compared to results from stage 3 and unbiased NEXRAD data. The uncorrected NEXRAD led to consistently overestimated peak discharge, whereas the corrected NEXRAD resulted in biases that were smaller and closer to zero (Figure 18). The average error in
magnitude of peak discharge was 842 ft$^3$/second, or an average of 20% of the observed flow, yielding a 572 ft$^3$/second and 5% improvement over Stage 2 flow results, respectively. The peak streamflow of all ten events were within the 50% hydraulic conductivity uncertainty bounds of the model, as compared to only five out of the twelve in the final stage of model development using observed precipitation. Although, the simulation of the peak magnitude improved, the average error in the timing of peak discharge for the verification was 8.8 hours, an increase of 5.8 hours over Stage 3. All simulation for individual events using the corrected Hydro-NEXRAD data are provided in Appendix A, Section A.3.

Figure 18. HEC-HMS model errors for each verification event using NEXRAD precipitation estimates. The x-axis shows the model error in timing of peak and the y-axis shows the model error in peak discharge, as a percent of observed peak discharge. The average error in timing and discharge are marked with the letter X for each data set.
6 Discussion

Although a number of calibration trials and iterations were necessary, post analysis reveals potential trends and behaviors that may be suitable for regionalization, and thus make implementation of the HEC-HMS model at additional forecast basins more efficient. Hydraulic conductivity was found to be the most sensitive parameters in the calibration, but published values resulted in the most accurate simulation results. Therefore, intensive automatic or manual calibration of this value is not recommended, although testing small adjustments is always prudent. Although the model errors were low when averaged across all events, the use of a range of hydraulic conductivity values would be a prudent approach to forecasting with the HEC-HMS given the variability in model accuracy from event to event. The lag time was found to vary linearly with the time since last precipitation, and could be easy to adjust in a forecast setting based on a simple equation if this relationship holds for other basins and a larger number of events. Although every effort was made to simplify the initial model calibration and time required to initiate the model for simulation, a number of data processing steps are still required, as summarized in Appendix C. The ArcMap models have been created to do much of the GIS work required to set-up the model implementation time should be further reduced.

Consistent patterns were observed with the GIS-derived NEXRAD data biases. Precipitation values nearest the confluence of both the Skunk River and Squaw Creek watersheds reflect estimates that were close to the observed values. Data also showed a trend towards increasing overestimation as the distance from the NEXRAD site increased (to the north). These patterns were observed with all algorithms and during both the spring 2007 and spring 2008 periods.
The strong relationship observed between previous precipitation events and the subbasin transform function lag time may also be applicable to other basins with similar soil types and land-use. Although the lag time would not be expected to change from event to event, the impact of tile drainage and other agricultural practices to the hydrologic cycle of the studied watersheds could be evident in calibrations through that parameter. The equation for the lag time multiplier adjustment by change from watershed to watershed, but we would expect the trend to be the same if this were the cause.

Each stage of calibration and verification of the HEC-HMS resulted in improved model performance for forecasting peak discharge. Stage 1, 2, and 3 of model development used gauged precipitation measurements and had peak flow errors averaging 46%, 40%, and 25%, respectively. When using NEXRAD precipitation estimates, peak flow errors averaged 65% (uncorrected NEXRAD) and 20% (corrected NEXRAD). Model performance in forecasting timing of peak did not improve as consistently. For stage 1, 2, and 3, the average error in timing of peak was 5.3hrs, 4.0hrs, and 3.0hrs, showing a decrease in error for each stage of model refinement. When NEXRAD precipitation estimates were used for model input, the error in timing of peak was 5.9hrs (uncorrected NEXRAD) and 8.8hrs (corrected NEXRAD), showing a lack of improvement between the remote-sensed data versus the in-situ data for the timing of peak flow. Further analysis of individual events and the precipitation time series is needed to better understand why the increased error in peak timing occurred.

In our study, automatic calibration routines did not always provide the most reliable parameter estimation during model development. Hydraulic conductivity in particular, the most sensitive Green & Ampt infiltration parameter, caused the most model error when based
off of values derived from automatic calibration. Manual adjustment of the parameter and use of accepted values from other studies appeared connected to improved model performance. Our experience with HEC-HMS model development therefore indicates that published soil property values, and sometimes manual calibration, may yield better results than automatic model optimization schemes built into the HEC-HMS with a study of this type.

The use of GIS to create bias corrections for remotely-sensed NEXRAD precipitation estimates has been shown to improve the accuracy of the HEC-HMS streamflow model’s predictions of the magnitude of peak streamflow on the two basins studied. The implementation of the bias correction scheme appears to have reduced the accuracy of the model’s prediction for timing of that peak streamflow, however. The significant increase in modeled peak flow performance noted from the implementation of bias-corrected NEXRAD precipitation estimates is intriguing, and suggests that simple scalar corrections of the remote-sensed data may be satisfactory in some streamflow models. Furthermore, results suggest that information about spatial distribution within the watersheds improves the estimate of basin averaged precipitation. NEXRAD data may be of particular usefulness as an input to models of watersheds that do not have dense precipitation gauge networks, although the GIS analysis used to create the correction scheme required such a network. If future studies of other watersheds show consistency in NEXRAD bias as a function of distance from the NEXRAD site, then GIS analysis may not be required in all model implementations.

The CAPPI 1.3km AGL algorithm appears to have the most consistency between subbasins in the study area, while the HiFi algorithm is the least consistent between
subbasins. Based on visual analysis, the NWS algorithm appears to have the least variability in its error between the three heavy precipitation events and the HiFi algorithm appears to have the most variability between these events. The algorithm with the least variability, spatially and between events, will likely be the most useful because it will be the easiest to adjust for biases with a scalar correction factor.

Another important factor discussed regarding the choice of NEXRAD algorithms was the computation time required for creating the ArcASCII files. The CAPPI 1.3km AGL and Pseudo-NWS PPS algorithms took the shortest time to complete processing for one full day’s worth of archived data, while the HiFi algorithm took at least three times as long to complete the same amount of processing. Since time can be a major factor when trying to forecast flash flooding, the best algorithm for this purpose would be either the Pseudo-NWS PPS or CAPPI 1.3km AGL.

Based on my investigations into the performance and computation time required to process the files for various NEXRAD precipitation estimate algorithms, either the CAPPI 1.3km AGL or the Pseudo-NWS PPS algorithm would be a the best choice for use in an operational flash flood forecasting situation. These algorithms have similar ranges of error between subbasins, and also have lower variability between events when compared to the HiFi algorithm. Based on the results of previous studies and my research, the CAPPI 1.3km AGL algorithm was selected for use with the HEC-HMS. Upon implementing this algorithm, a significant improvement in streamflow forecasting ability was noted with respect to the number of precipitation events that produced streamflow peaks that fell within the model uncertainty bounds, which increased from a rate of 50% to 100%. Timing of peak
did not improve, but the error in magnitude of peak discharge improved significantly (Figure 18). Modeled streamflow reached peak discharge sooner on average when compared to observed streamflow. The average magnitude of peak discharge was also underestimated when compared to observations. Changes to the bias correction scheme could be made in an attempt to reduce these possible remaining biases.

In the future, further verification of the model should be done at a local National Weather Service Forecast Office, where it can be fully tested in an actual operational setting. Operational forecasts using the HEC-HMS model should be created and compared to that of current forecasting techniques. Doing so will add an important perspective to the model analysis process from the location where it is most likely to be implemented, if proven successful. Comparison of computation time, ease of use, and data management simplicity between the HEC-HMS and current methods would be important when considering the addition of this new modeling technique. An attempt at using the HEC-HMS methodology described here and comparing the results to the currently-operational SAC-SMA model forecasts was conducted and is described further in Appendix B.

The support staff for the Hydro-NEXRAD project has indicated that data availability gaps will likely be filled in during future months, as funding allows. Doing so will allow more time periods to be available for download, and could eliminate the problem with the NEXRAD switch to super resolution data that caused events after May 2008 to be unavailable to radar precipitation driven model runs. Based on results shown here, a longer period should be used in the analysis and that doing so will increase the accuracy of the bias correction scheme. Doing so will remove possible event-to-event variability in the
performance of the NEXRAD precipitation estimates and reduce the effect of potential outlier events. When more data becomes available from future high precipitation events in the Skunk and Squaw watersheds, more GIS interpolation could be conducted to check for consistency with results from this study.
7 Conclusions

The HEC-HMS model was calibrated and verified using observed precipitation data for the purpose of examining its use as an operation flash flood forecasting tool by National Weather Service forecasters. Many stages of model development were required to obtain an adequate calibration of the model. During each step, an improvement in forecasting both the timing and value of the streamflow peak was observed. The model was then run using simple bias-corrected NEXRAD data. A decrease in model error of the streamflow peak value was observed, but the error in modeled timing of the peak increased. After implementing the bias correction scheme, the model run with NEXRAD precipitation estimates appeared to have a slight peak discharge under-estimation tendency. On average, the model also forecasted the timing of peak discharge sooner than observed.

Preliminary results are encouraging for the application of HEC-HMS in operational forecasting, particularly if uncertainty bounds on the hydraulic conductivity are applied. Several potential simplifications to the modeling procedure were identified which would reduce the time required for initial model set-up at new sites. The biggest obstacle to implementation of the HEC-HMS will likely be the time required for data processing prior to running the model simulation in order to produce a forecast.
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References


Appendix A: HEC-HMS Model Output Graphs

A.1 Stage 3 Verification

The following section contains figures from each significant precipitation event used for HEC-HMS verification during Stage 3 of model development (Section 4.4).
Note: preceding figures were from HEC-HMS model runs not used in the final analysis. The figures represent model output when an alternate set of transform lag times were used. A rainfall event of just over 0.25 inches occurred just prior to this rainfall event, thus reduced lag times were used (see section 4.3 for further description of the lag time adjustment methodology). When that marginal rainfall event was skipped and the next prior event was used, the lag times were reduced significantly and the preceding figures resulted.
May 7-10th, 2008: Modeled vs. Observed, LincolnWay Gauge

May 7-10th, 2008: Modeled vs. Observed, Riverside Gauge
Note: preceding figures were from HEC-HMS model runs not used in the final analysis. The figures represent model output when an alternate set of transform lag times were used. A rainfall event of just over 0.25 inches occurred just prior to this rainfall event, thus reduced lag times were used (see section 4.3 for further description of the lag time adjustment methodology). When that marginal rainfall event was skipped and the next prior event was used, the lag times were reduced significantly and the preceding figures resulted.
May 30th-June 2nd, 2008: Modeled vs. Observed, LincolnWay

May 30th - June 2nd, 2008: Modeled vs. Observed, Riverside
June 3-5th, 2008: Modeled vs. Observed, LincolnWay Gauge

June 3-5th, 2008: Modeled vs. Observed, Riverside Gauge
June 8-11th, 2008: Modeled vs. Observed, LincolnWay Gauge

June 8-11th, 2008: Modeled vs. Observed, Riverside Gauge
June 12-14th, 2008: Modeled vs. Observed, LincolnWay Gauge

June 12-14th, 2008: Modeled vs. Observed, Riverside Gauge
A.2 Un-corrected NEXRAD

The following section contains figures from each significant precipitation event used for HEC-HMS verification during Stage 3 of model development (Section 5.0).

April 24-28th, 2007: Modeled vs. Observed, LincolnWay Gauge

April 24-28th, 2007: Modeled vs. Observed, Riverside Gauge
May 6-9th, 2007: Modeled vs. Observed, LincolnWay Gauge

Discharge (cfs)

Time beginning May 6th, 2007, 12:00AM

May 6-9th, 2007: Modeled vs. Observed, Riverside Gauge

Discharge (cfs)

Time beginning May 6th, 2007, 12:00AM
May 23-28th, 2007: Modeled vs. Observed, LincolnWay Gauge

Time beginning May 23rd, 2007, 12:00AM

May 23-28th, 2007: Modeled vs. Observed, Riverside Gauge

Time beginning May 23rd, 2007, 12:00AM
April 23-26th, 2008: Modeled vs. Observed, LincolnWay Gauge

April 23-26th, 2008: Modeled vs. Observed, Riverside Gauge
May 6-10th, 2008: Modeled vs. Observed, LincolnWay Gauge

Discharge (cfs)

Time beginning May 6th, 2007, 12:00PM

May 6-10th, 2008: Modeled vs. Observed, Riverside Gauge

Discharge (cfs)

Time beginning May 6th, 2007, 12:00PM
A.3 Bias-corrected NEXRAD

The following section contains figures from each significant precipitation event used for HEC-HMS verification during Stage 3 of model development (Section 5.1).

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**April 24-28th, 2007: Modeled vs. Observed, LincolnWay Gauge**

![Graph showing modeled vs. observed discharge for LincolnWay Gauge]

**April 24-28, 2007: Modeled vs. Observed, Riverside Gauge**

![Graph showing modeled vs. observed discharge for Riverside Gauge]
May 6-9th, 2007: Modeled vs. Observed, LincolnWay Gauge

Time beginning May 6th, 2007, 12:00AM

May 6-9th, 2007: Modeled vs. Observed, Riverside Gauge

Time beginning May 6th, 2007, 12:00AM
May 23-28th, 2007: Modeled vs. Observed, LincolnWay Gauge

May 23-28th, 2007: Modeled vs. Observed, Riverside Gauge
April 23-26th, 2008: Modeled vs. Observed, LincolnWay Gauge

April 23-26th, 2008: Modeled vs. Observed, Riverside Gauge
May 6-10th, 2008: Modeled vs. Observed, LincolnWay Gauge

May 6-10th, 2008: Modeled vs. Observed, Riverside Gauge
Appendix B: April 25-27, 2009, Operational HEC-HMS Forecast

B.1 Introduction

The HEC-HMS was run in an operational manner for a significant rainfall event and then compared against model output from the SAC-SMA model run by the North Central River Forecast Office (NCRFC). The precipitation started on April 25\textsuperscript{th}, 2009, and ended on April 27\textsuperscript{th}, 2009. The streamflow was modeled from April 26\textsuperscript{th}, 2009, to May 1\textsuperscript{st}, 2009.

B.2 Model Setup

NEXRAD precipitation estimates were unavailable from the Hydro-NEXRAD system at the time of this event, so the model setup from Stage 3 (Section 4.2) was used. A gap in rainfall values from the City of Ames Alert network data for all but one gauge started at 10:15pm on April 26\textsuperscript{th} and ended at various times of the day on April 28\textsuperscript{th}, depending on the precipitation gauge. Because of this, estimated precipitation had to be used for all the remaining stations for a roughly 5 hour period during this gap (Figure 19). To create the precipitation estimate, available data for that period from the East Boone County gauge was used for the other gauges and was adjusted based on variability in the daily NEXRAD precipitation estimate obtained from the Iowa Environmental Mesonet (http://wepp.mesonet.agron.iastate.edu/GIS/rainfall.phtml?option=daily&pvar=rainfall\_in&dstr=04/26/2009). For example, if the grid cell over the East Boone County gauge estimated precipitation of 2” and the grid cell over a gauge with missing data estimated 1”, and then 0.5 was multiplied to each time-step of the data before it was used for the other gauge. Most subbasin-averaged precipitation was based on actual observations, but a significant percentage was based on the estimations from the one available dataset. In the E18Skunk basin, for example, 27% of the precipitation by volume was from the estimation technique described above.
Soil moisture data from the Ames SCAN site was available for the hour prior to precipitation onset. A WEPP model soil moisture shapefile was available from the April 26th run, but that data was valid for April 25th. The WEPP values were adjusted by the SCAN site data using the procedures described in Section 2.2. No rainfall exceeding 0.25” occurred over the watersheds in the 18 days prior to this event, so the maximum lag time multiplier of 1.3 was applied to each subbasin (See section 4.3).

**B.3 Model Output Comparisons**

The SAC-SMA model was run by the NCRFC numerous times during the event. Model forecasts from the SAC-SMA run before the end of the precipitation event used forecasted precipitation along with the observed precipitation to drive the model. The HEC-HMS was run with only observed precipitation. The model runs for the SAC-SMA were issued at 9:36am and 8:28pm on April 26th, and 2:13am and 9:34am on April 27th. The model runs for the HEC-HMS were completed at 9:00pm on April 26th and 3:00am on April 27th. The first HEC-HMS run was done before any estimated precipitation values were...
required by the model, and the second HEC-HMS run was done after the precipitation event ended. River stage forecasts for both the LincolnWay (Figure 20) and Riverside (Figure 21) gauges were analyzed.

In both watersheds, the SAC-SMA forecasts from the NCRFC generally overestimated the river stage, but this overestimation was particularly significant in the LincolnWay watershed. Errors in modeled peak stage of the event ranged from a near 100% overestimate in the April 26th 9:36AM forecast to near 33% in the April 27th 9:34AM forecast at that gauge. The last SAC-SMA forecast began after all precipitation had ended and after the peak at LincolnWay gauge was observed. Each forecasted peak was above the flood stage of 9ft set by the NWS DMX forecast office.

In the Riverside watershed, the observed river stage was overestimated by the 9:36AM and 8:28PM forecasts of the SAC-SMA model on April 26th. The forecasts made on April 27th were very close to that of the observed stage. The only SAC-SMA forecast from the NCRFC to reach the flood stage of 14ft at the Riverside gauge was the one issued at 9:36AM on April 26th.

The likely explanation for the significant overestimation errors in the SAC-SMA forecasts issued by the NCRFC was forecaster error (Jeff Zogg, NWS DMX, personal communication, 2009). The precipitation of the event was skewed towards the mouth of both watersheds. This caused the standard unit hydrograph to no longer be valid, as a major assumption of the unit hydrograph is uniform rainfall intensity across the entire modeled watershed. To correct for this, the unit hydrographs would need to be skewed so that streamflow response and the subsequent peak stage occurred sooner. The forecaster instead attempted increase the conceptualized moisture content in the upper soil layers to compensate for an early model underestimation. The consequence of this action, however, was a significant peak stage overestimate.

The two sets of HEC-HMS runs both slightly underestimated the peak stage of the event. Also, because the standard SCS unit hydrograph is used as the model’s transform function, no adjustment to the unit hydrograph was made for the skewed precipitation nearest
the mouth of the watersheds. Some of this should have been taken into account due to the distributed nature of the model, however. The April 26\textsuperscript{th} 9:00PM run of the HEC-HMS did not include the last 5 hours of precipitation, which contributed to the underestimation of that model run. When the April 27\textsuperscript{th} 3:00AM run was computed, all of the precipitation had fallen and the observed peak stage was captured by the hydraulic conductivity uncertainty bounds in both watersheds. Only the 0.08 in/hr hydraulic conductivity run of the HEC-HMS for the LincolnWay watershed indicated a river level exceeding flood stage. It should also be noted that because the soil moisture data from the WEPP model was valid April 25\textsuperscript{th}, and thus did not include the soil moisture increases from rainfall on April 26\textsuperscript{th}, some underestimation in the runoff to streams was likely to have occurred in the model.

More operational runs and analysis of the HEC-HMS are needed to show consistency in results. At this time, it appears as if the model has a tendency to underestimate streamflow forecasts when compared to observations. If this continues with future operational forecasts, the 0.23 in/hr and 0.19 in/hr uncertainty bounds could be removed, leaving the two model runs with higher flow that are generally closest to the observations. The HEC-HMS still needs to be set-up for other basins to test for basin-to-basin consistency.
Figure 20. Forecasts of river stage at the LincolnWay gauge from both the SAC-SMA and HEC-HMS models for the April 25th-27th precipitation event.
Figure 21. Forecasts of river stage at the Riverside gauge from both the SAC-SMA and HEC-HMS models for the April 25th-27th precipitation event.
Appendix C: HEC-HMS Modeling Setup Procedures

The following is a description of the steps required to set-up a HEC-HMS model as was done to complete the preceding report.

C.1 Obtaining/Analyzing Basin Data

Delineating Subbasins

1. Download digital elevation model (DEM) data at the 1/3 arc-second resolution for the area of interest from the USGS Seamless server, http://seamless.usgs.gov/index.php. Import DEM raster(s) into ArcMap. If more than one DEM raster is required to cover the area of interest, use the “mosaic” function to create a single raster.
2. In ArcCatalogue, create a point shapefile for each of the streamflow gauges within the area of interest. Edit this file with ArcMap to add a point to each file at the location of the gauges.
5. Select Spatial Analyst Tools -> Hydrology -> Watershed. Create a watershed polygon shapefile for each subbasin by repeating this step with each file created in Step 2. If more than one polygon shapefile is created on the same stream or river in a watershed, some polygons will overlap. Remove the overlapping area by using the Analysis Tools -> Overlay -> Erase function.
6. Use the Measure tool to select each subbasin and determine their areas.
Calculating Initial Abstraction and Impervious Area

1. Download canopy cover data percent imperviousness data for the area of interest from the USGS Seamless server. Import rasters into ArcMap.
2. Select Spatial Analyst Tools -> Zonal -> Zonal Statistics. Use the percent imperviousness raster as the input value raster and a subbasin extent polygon shapefile for the feature zone data. Repeat for each subbasin. The output raster contains the mean value of imperviousness over the entire subbasin.
3. Determine the relative canopy abstraction in inches for the average tree type of the area. Use raster calculator to multiply this value by the canopy cover raster. The resulting raster is the depth of rainfall at each pixel held by vegetation leaf area that must be met before precipitation reaches the ground.
4. Select Spatial Analyst Tools -> Zonal -> Zonal Statistics. Use the canopy cover abstraction raster from Step 3 as the input value raster and a subbasin extent polygon shapefile for the feature zone data. Repeat for each subbasin. The output raster contains the mean value of canopy abstraction over the entire subbasin.

Calculating Soil Parameters for Green & Ampt Equation

1. For our study, we used a combination of WEPP model data, calibrations, and published values to determine soil parameters such as hydraulic conductivity. Book values will likely be adequate, but modeled output from the WEPP model can be used if available. Download time series of hydraulic conductivity and wetting front suction head for each township covered by subbasins in the watershed of interest.
2. Average the time series data points at each day of year over all the years available.
3. Weight the daily average time series data based on what townships, and how much of those townships, are within the bounds of each subbasin.
4. Average the wetting front suction head and hydraulic conductivity values over the entire spring and summer periods for each subbasin.
5. Soil moisture data can also be obtained through the WEPP in shapefile format. These shapefiles were adjusted based on a nearby Soil Climate Analysis Network.
(SCAN) site data. To view all sites available, visit http://www.wcc.nrcs.usda.gov/scan/. To retrieve data from sites in the Iowa area, visit http://mesonet.agron.iastate.edu/scan/.

6. The WEPP shapefile of soil moisture contain a data set for the 0-10cm soil layer and the 10-20cm soil layer. These shapefiles were both converted to rasters, then were averaged together using raster calculator. Then the resulting soil moisture value was adjusted based on the difference in soil moisture between the nearest SCAN site and the WEPP estimate.

7. The soil moisture raster was then divided by the average soil porosity. The reciprocal of this value is the soil moisture deficit required by the Green & Ampt infiltration equation.

Creating Bias Correction Factors for NEXRAD Precipitation Estimates

1. The NEXRAD precipitation estimates to be used as input to the HEC-HMS should be summed up over a significant period of time. The summed data should then be put onto a raster grid to use in ArcMap. For our study, we used rainfall estimates over both the spring months of 2007 and 2008.

2. A shapefile containing the locations of all available rainfall gauges should be created in ArcCatalog. In ArcMap, a field should be added to the shapefile’s attributes table. Observed precipitation values for each of the rain gauges should be entered.

3. Using the tension-spline interpolation, a raster should be created of the observed precipitation values.

4. The difference between the NEXRAD estimates and the precipitation observations over the same period should be calculated. The difference between the NEXRAD and the observations should then be averaged over each subbasin using the Zonal Statistics function.

5. A bias correction factor should be calculated as described by Equation 3.

6. The bias correction factor should be multiplied by the NEXRAD precipitation estimates at each timestep before being used in the HEC-HMS model.
Entering Data into HEC DSS Files

1. DSS files are the file format used by HEC-HMS and provide a convenient way to store precipitation and discharge data from gauges in the watershed. To edit DSS files, use HEC’s DSSVue, available at [http://www.hec.usace.army.mil/software/hec-dss/hecdssvue-dssvue.htm](http://www.hec.usace.army.mil/software/hec-dss/hecdssvue-dssvue.htm)

2. Create a new DSS file specifically for storing observed data for each watershed model.

3. Use the manual data entry function (Utilities -> Manual Data Entry -> Time Series) to enter in data to the file.

4. Plug-ins are available on the HEC DSSVue website that can retrieve data from Excel spreadsheets and import them into DSS files.

C.2 Creating HEC-HMS Model

Creating the Basin Model

1. Use Basin Model Manager to create a new basin inside the project file.

2. Use the subbasin tool to create a subbasin in the model for each delineated subbasin.
   a. For each subbasin, enter the GIS-derived area, and select the modeling methods.
   b. Green & Ampt should be selected for the Loss Method.
   c. SCS Unit Hydrograph should be selected for the Transform Method.
   d. Recession should be selected for the Baseflow Method.

3. Use the junction tool to place simulated stream junctions or gauge locations into the model.

4. Use the reach tool to create open channel reaches. A reach should be used whenever water from one subbasin must flow through another subbasin to reach the watershed outlet. Reaches should be set to the Muskingum method.
5. Enter in the soil parameters for each of the subbasins, as calculated in Section C.1.
6. Reach routing parameters, transform function lag time, and baseflow recession parameters can be derived from empirical methods or calibration.
7. Once the model is set up, use the Meteorological Model Manager to create a precipitation analysis method. Use specified hyetograph for NEXRAD precipitation estimates or Gage Weights (Thiessen polygons) for observed rain gauge precipitation.
8. Use the Control Specifications Manager to create a model run. Specify the desired temporal resolution and start/end times.
9. Use the Time Series Data Manager to add precipitation gauges and discharge gauges to the model. Set each gauges data source to the DSS file used to store the data.
10. For more detailed help on setting up a model using HEC-HMS, use the documentation available by clicking Help -> User’s Manual

C.3 Running the Model

1. Create a model run by going to Compute -> Create Simulation Run. Select the basin model, meteorological model (this allows you to create a different simulation run for gauge precipitation and NEXRAD precipitation), and the control specifications.
2. The run the model, go to Compute -> Select Run -> [Created Model Run]. Then click the Compute Current Run button.
3. To view model output data, right-click on subbasins, reaches, or junctions. Data can be viewed as a graph or a table that can be copied and then pasted into an excel spreadsheet.
4. Calibration may also be done using the HEC-HMS by following Step 1 but instead of creating a simulation run, creating an optimization trial instead.