THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

DEPARTMENT OF METEOROLOGY

ASSESSING THE RIVER FORECASTING CAPABILITIES OF THE FLUX-PENN STATE INTEGRATED HYDROLOGIC MODEL AND THE ANTECEDENT PRECIPITATION INDEX-CONTINUOUS MODEL FOR THE LITTLE JUNIATA RIVER BASIN

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ABSTRACT

Researchers have maintained discussion regarding the effectiveness of distributed, physical hydrologic models as river forecasting tools compared to the lumped, conceptual models currently used prevalently in the National Weather Service River Forecasting Centers. We assess the river forecasting capabilities of the distributed, physically-based Penn State Integrated Hydrologic Model, coupled with the Noah land surface model (Flux-PIHM), in comparison to the lumped, conceptual Antecedent Precipitation Index (API)-Continuous model. We produce and analyze reanalysis model discharge output from Flux-PIHM and the API-Continuous model for the year 2010 at the Spruce Creek stream flow gauge in the Little Juniata River Basin in Central Pennsylvania. Twelve precipitation events were selected from the year 2010 for further analysis. We evaluate, in relation to USGS stream flow observations, each model's ability to accurately simulate peak discharge magnitude during a storm event, the elapsed time between the start of the event and the occurrence of the peak discharge value and the total runoff. We also compare multiple precipitation datasets to determine the effects that alternative forcing data may have on model output. Results indicate that, among other trends, Flux-PIHM overestimates base flow and peak discharge during the winter months while more accurately simulating peak discharge in the summer months compared to API-Continuous. Furthermore, both models simulate shorter time to peak discharge compared to observations for a majority of the events. Many of the possible causes for the identified trends in this study point to a need for various improvements to Flux-PIHM and API-Continuous calibration and parameterization.

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Chapter 1

Introduction

During the last decades, due in part to increases in computing power, scientists have continued to develop hydrologic models of greater complexity in an attempt to best mimic the natural processes governing the movement of water within a basin. In recent years the field of hydrology has focused on determining whether applying these more complex models to an operational river forecasting setting is worthwhile and feasible (Clarke et al., 2008).

Hydrologic models are generally grouped into two categories: lumped or distributed models. In lumped models, spatial variation is ignored and the entire basin of study is considered to be one unit. These models are normally designed to simulate stream flow at a basin outlet only (Moradkhani & Sorooshian, 2008). The earliest lumped models relied solely on techniques such as the unit hydrograph theory and the Nash linear cascade of reservoirs model (Solamatine & Ostfeld, 2008). Conversely, distributed models account for the spatial variation of parameters and variables within a basin (Moradkhani & Sorooshian, 2008). Distributed models can create simulations for interior points in a basin and ungauged sites (Smith et al., 2004a). Distributed model development has benefited from a growing availability of spatially variable meteorological data.

Hydrologic models can also be identified based on the complexity with which they represent the driving processes of the water cycle. On one end of the spectrum are empirical models, based on relationships between input and output time series. These models solely use basic statistical techniques such as linear regression (Solamatine & Ostfeld, 2008; Kampf, 2006). Models, generally those with some intermediate level of complexity, can also be classified as conceptual. Conceptual models are highly parameterized and contain some representation of the natural processes at hand. Both lumped and distributed conceptual models exist. Finally, models can be categorized as physically based. The physical approach offers the most detailed representation of hydrological processes, using partial differential equations to represent and simulate the various interactions and processes within a basin (Moradkhani & Sorooshan, 2008). Examples include the Michael B. Abbott Systéme Hydrologique Européen (MIKE SHE) model and the River Basin Simulation Model (RIBASIM) (Solamatine & Ostfeld, 2009), as well as the Penn State Integrated Hydrological Modeling System. The increase in model sophistication over past decades has enhanced the detailed nature of physically based models, but as Beven (1989) emphasizes, even the most complex models are still an extreme simplification of reality.

Given the various types of models available, a point of debate in the scientific community has been determining which technique is most beneficial for river forecasting, and for what scenarios. Several studies have been conducted to offer some response to this question. The National Weather Service (NWS) Office of Hydrologic Development has compared a collection of distributed models to the lumped, conceptual models used for river forecasting today. The study, the Distributed Model Intercomparison Project (DMIP), was conducted in two phases. Phase 1, completed in 2004, is outlined in Smith et al., (2004a) and Phase 2, completed in 2011, is outlined in

Smith et al., (2012a). In Smith et al., (2012b), the DMIP experimenters concluded that although distributed models have improved as a river forecasting tool, these models only outperformed the lumped models in some cases.

Inspired in part by DMIP, this study will compare model output of discharge from the distributed, physically based Penn State Integrated Hydrologic Model (PIHM), which has been coupled with the Noah Land Surface Model to form Flux-PIHM, and output from the lumped, conceptual Antecedent Precipitation Index (API)-Continuous model to USGS discharge observations for 2010 at the Spruce Creek stream flow gauge in the Little Juniata river basin, an 843.3 km^2 basin in Central Pennsylvania. We will assess the ability of each model to represent the physical processes of the basin by comparing various characteristics of discharge hydrographs from 12 selected storm events. The magnitude of the discharge peak, the elapsed time between the start of a precipitation event and the peak of the responding discharge and the amount of runoff produced is analyzed. Similar indices were analyzed in DMIP. We suspect that amongst all atmospheric forcing fields necessary to run the models, precipitation may have the most prominent effect on the characteristics of resultant discharge. The importance of quality precipitation forcing data is emphasized in Lou et al., (2003). We will assess whether the magnitude and duration of specific precipitation events differs between forcing data sets and if so, whether these discrepancies can explain any of the differences identified in discharge model output.

This study employs some of the analysis techniques used in DMIP, such as an analysis of the peak discharges in storm events. DMIP, however, compared multiple distributed models on 16 different basins ranging in area from 37km^2 to

2484km^2 using multiple years of data, while this study analyzes just one distributed model on a single basin. DMIP does not include a comparison of precipitation data sets, which will be used in this study to further explore the scientific reasoning behind our results. Additionally, DMIP uses the same forcing data for all models in the study while our study uses data sets that maximize performance of each model, a practice that would be conducted in a true forecasting setting. This study is not wide enough in scope to concretely determine whether distributed models are generally more effective river forecasting tools. This study will, however, assess model inconsistencies and offer possible explanations that can be taken into consideration for model improvement as the operational river forecasting field considers a transition towards the use of distributed models.

Chapter 2

Methods

2.1 Domain of Study

The Little Juniata river basin (Figure 2.1) is located in central Pennsylvania just west and south of State College, PA. It is a second order watershed 843.3 km^2 in size and consists of 18% developed land, 17% agriculture, 63% wooded, and 2% transitional land (Capracasa, 2005). The basin has a mean elevation of 408.4m and a channel slope of 2.82 m/km. It lies within the Juniata River watershed, which in turn is a tributary of the Susquehanna River watershed.

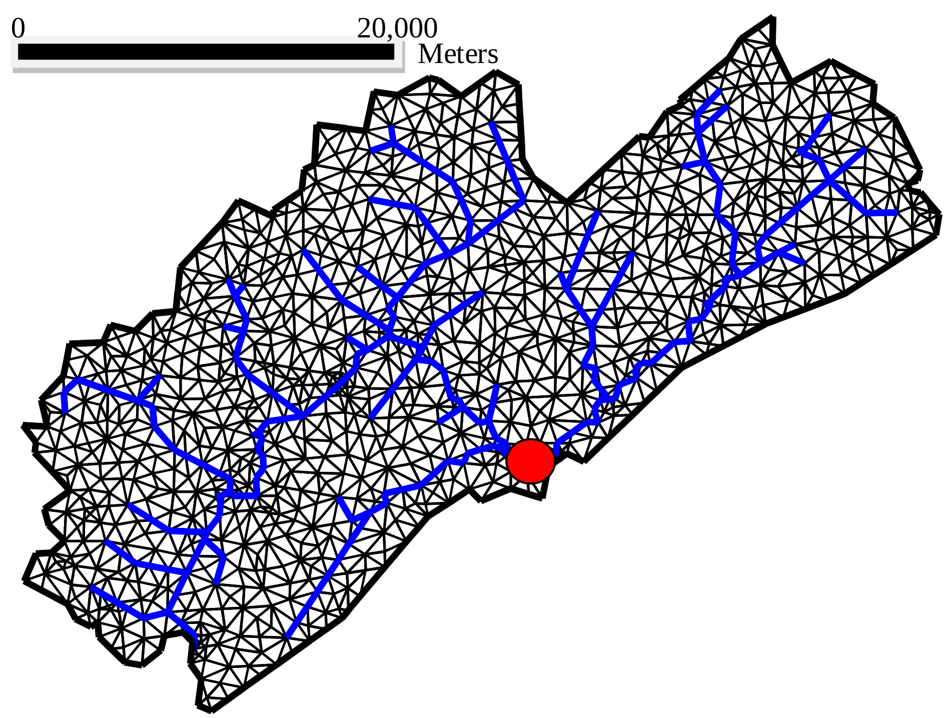


Figure 2.1. A schematic of the Little Juniata river basin as represented by the Flux-PIHM model. The red dot indicates the approximate location of the Spruce Creek stream flow gauge. Flux-PIHM partitions the domain into triangles instead of grid points.

We selected the Little Juniata river basin for this study because it serves as a larger sized basin than the basin on which Flux-PIHM was previously tested, the nearby 0.08 km^2 Shale Hills basin (Shi et al., 2013). Due to the larger area, Little Juniata is more relevant for river forecasting purposes. Within the Little Juniata river basin lays the Spruce Creek streamflow gauge (USGS 01558000), which serves as a forecast point for the NWS Middle-Atlantic River Forecast Center. This study compares model output for the Spruce Creek gauge with discharge observations at the same location for the year 2010.

2.2 Storm Events

We selected twelve storm events (Table 2.1) for statistical analysis, including one storm for each month in 2010. For brevity storms will be referred to by the unique month in which they occurred.

	Start Date	Total Precipitation (cm.)	Precipitation Duration (hrs)
1	17 January 2010	1.8796	15
2	5 February 2010	3.048	30
3	12 March 2010	6.604	64
4	25 April 2010	0.889	9
5	22 May 2010	2.1336	30
6	9 June 2010	3.6322	16
7	20 July 2010	1.905	8
8	6 August 2010	0.19386	6
9	30 September 2010	9.1694	24
10	18 October 2010	0.3302	18
11	4 November 2010	1.524	25
12	12 December 2010	0.7112	19

Table 2.1. The selected storm events for analysis, including the start date of the precipitation, the total precipitation (cm) for the event, and the number of hours precipitation occurred. Note: one storm event per month.

Selection of the storm events was a partially subjective process. We attempted to use storm events with a variety of precipitation totals. We conducted a visual analysis of the precipitation data around the time of the storm to estimate the amount of associated precipitation and to attempt to ensure that the discharge profiles would not be too heavily influenced by precipitation events preceding our succeeding the event of choice. Along with the precipitation data associated with the storm, the discharge profiles, known as hydrographs, were collected from the PIHM output, API-Continuous output and the USGS observations for comparison.

2.3 Model Background, Forcing Data and Output

2.3.1 Penn State Integrated Hydrologic Model

The Penn State Integrated Hydrologic Model is an open-source community model tied to a GIS interface which allows users to digitally download the parameters and data necessary to run the model for a river basin of choice. PIHM is a multi-process model governed by a set of partial differential equations to represent the routing and flow of surface and subsurface water, and a set of ordinary differential equations to represent physical processes in the basin, such as evapotranspiration and canopy interception. The model uses irregularly sized triangles in a grid to cover a given domain. Readers are referred to Qu & Duffy, (2007) or the website dedicated to PIHM (www.pihm.psu.edu) for a more detailed explanation of the model. For this study we use a version of PIHM which has been coupled with the Noah land surface model (LSM) (Ek et al., 2003) in order to take advantage of the LSMs superior evapotranspiration scheme. This version of PIHM is referred to as Flux-PIHM. The design of Flux-PIHM is explained in Shi et al., (2013).

It is necessary to calibrate model parameters in order to ensure the model is properly tuned to the specific domain for which it is being executed. The process helps the model perform as accurately as possible. For this study, PIHM alone was calibrated before being coupled to Noah as Flux-PIHM. The process used to calibrate PIHM to the Little Juniata river basin involved first separating the “fast” parameters, which control processes on time scales of minutes, hours and days, from the “slow” parameters, which control processes on month-long to season-long time scales. A process known as the Covariance Matrix Adaptation Evolutionary Strategy (Hansen & Ostermeier, 2001;

Hansen et al., 2006) was employed to optimize the fast and then slow parameters as one batch, and assigning values to, and rescaling the parameters in, each group. Flux-PIHM is then run with those parameters and the root mean squared error of the modeled output versus observational data is analyzed. The parameters are rescaled and the root mean squared error is recalculated until the user reaches a sufficient number of trials or a desired error criterion (Y. Shi, personal communication).

The model calibration was performed to best match hourly model output of discharge with discharge observations in the Little Juniata River basin. Specifically, hourly discharge observations from two rain events in September of 2004 were used for this optimization. These storms were large discharge events associated with remnants of hurricanes (Y. Shi, personal communication).

Flux-PIHM requires a collection of forcing datasets in order to adapt to the spatial and temporal variability of the basin. Time series of precipitation, temperature, relative humidity, wind speed, downward shortwave radiation, downward longwave radiation, and surface pressure for the period and area of study were gathered from the forcing data used in Phase 2 of the National Land Data Assimilation System (NLDAS-2). We acquired the datasets though the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC) Mirador database at http://mirador.gsfc.nasa.gov/. Using forcing data similar to what we collected, NLDAS-2 executes four land-surface models – Noah, Mosaic, Sacramento Soil Moisture Accounting (SAC-SMA), and the Variable Infiltration Capacity (VIC) model – to provide output over a domain covering the entire continental United States at a spatial resolution of 1/8-degree. Xia et al., (2012) and Mitchell et al., (2004) provide more detailed accounts of NLDAS-2 and its predecessor, NLDAS-1, respectively. Information is also available at the webpage dedicated to NLDAS-2, http://ldas.gsfc.nasa.gov/nldas/NLDASnews.php.

For this study, Flux-PIHM was run at a one-hour time scale and output was analyzed at the same temporal resolution. Simulations were conducted for 1 January 2009 to 1 January 2011. The first year was used as a model spin-up period to reduce any initial condition problems. While Flux-PIHM produces a variety of energy and hydrologic related output, this study only utilizes model derived longitudinal flow. The longitudinal flow product is equivalent to river discharge and will be referred to as such hereafter. We gathered hourly model discharge in m^3/day from 1 January 2010 at 0z to 1 January 2011 at 0z for Flux-PIHM's 59^{th} river segment, which corresponds to the Spruce Creek stream flow gauge.

We also compared the amount of runoff observed and estimated by the models for a given storm event. Before the ground is saturated, all water from precipitation percolates underground and contributes to the subsurface component of runoff known as base flow. Once the surface, and the soil just below the surface, is saturated, any additional precipitation contributes to surface flow, and is termed runoff. In order to calculate runoff, the base flow component was removed from the discharge hydrographs. The base flow value was assumed to be the discharge value at the start of the precipitation event. This amount was subtracted from every discharge value to produce a time series of Flux-PIHM modeled runoff for each storm event.

2.3.2 Antecedent Precipitation Index-Continuous Model

The Antecedent Precipitation Index-Continuous model, referred hereinto forth as API-Continuous, is a lumped, conceptual model used by the National Weather Service Middle Atlantic River Forecast Center to forecast stream flow and stream stage at sites across the mid-Atlantic region. In this model, precipitation input is used to calculate an Antecedent Precipitation Index, a weighted sum of the precipitation prior to the start of a high-flow event. The index is calculated based on the notion that the effects of antecedent precipitation on discharge decays with time (Beschta, 1990). The calculation of this index considers the magnitude and duration of observed or estimated precipitation before a potential high-flow event, as well as the geological and topographical characteristics of the basin. The model uses four quadrants, or equations, to produce output. In order, the quadrants account for the time of year, account for the surface moisture conditions, compute the surface runoff based on surface and soil-moisture conditions, and compute the fraction of precipitation that will be directed to groundwater storage. A soil moisture index is determined, not with soil moisture forcing data, but by defining how much precipitation is needed to induce surface runoff in the basin, which only occurs when the soil is completely saturated. The model can also account for the effects of frozen ground. The model is calibrated to limit the error between the model estimated discharge and observed discharge on a six hour timescale. The calibration process uses multiple years of data compiled together in order to accurately represent normal seasonal conditions. In an operational setting, API-continuous may be hand tuned in real time to match observations, however no hand tuning was performed to the forcing or output used in this study (C. Moser, personal communication). Readers are referred to

Continuous API Model, (2002) and Sittner et al., (1969) for more detail about the API-Continuous model. It is not possible to execute API-Continuous outside of the River Forecast Center, so the model was executed by hydrologists at the Middle Atlantic River Forecast Center, and model output and forcing data was provided to the investigators.

Forcing data for the API-Continuous model includes potential evaporation, mean areal precipitation and mean areal temperature. All forcing data for the model was developed with local observations.

API-Continuous was run on a six-hour time scale from 1 September 2003 to 30 April 2012, although only output from 1 January 2010 to 1 January 2011 was used for analysis in this study. An array of variables related to discharge and runoff are output by API-Continuous but this study only uses total flow (base flow and surface flow) in m^3/s, which is equivalent to discharge. Values were converted to m^3/day to match the units of the Flux-PIHM discharge output. Following the practice implemented for Flux-PIHM, runoff-only hydrographs were calculated for each storm by subtracting the base flow value, assumed to be the discharge value at the start of a precipitation event, from each discharge value in a given storm hydrograph.

2.4 Observational data

The United States Geological Survey (USGS) maintains a network of water resource data, including stream flow gauge data for the Spruce Creek outlet. 15-minute stream discharge data was gathered from the USGS Water Data site (http://waterdata.usgs.gov/usa/nwis/uv?site_no=01558000) for 1 January 2010 to 1 January 2011. We converted the observation discharge units of ft^3/sec to m^3/day to match the units of the Flux-PIHM output. Finally, the timestamps were adjusted from

EST and EDST to UTC. Observed runoff-only hydrographs were produced by removing the base flow from each discharge value associated with a given storm event.

2.5 Basin Flow Analysis Techniques

We utilized a variety of variables and measures to compare the hydrographs of Flux-PIHM and API-Continuous to the respective observations in an attempt to analyze the accuracy of the models as river forecasting tools. Some of the statistical tests and measures designed were inspired by those used in the first phase of the DMIP study and outlined in Reed et al., (2004).

In addition to extracting modeled and observed discharge hydrographs for each storm, we developed residual hydrographs, which display the error of each Flux-PIHM and API-Continuous hydrograph from the corresponding observation hydrograph for a given storm. Base flow was removed from each hydrograph time series, and the residual was calculated by subtracting the model output values from the observations.

The peak discharge of a storm event correlates to the highest water level during the event, and therefore is a noteworthy parameter for river forecasting. An under-forecasted peak discharge magnitude may result in a missed forecast for a flood event. Similarly, the elapsed time between the start of a precipitation event and the peak of the discharge is a valuable measure for river forecasting. It is also a good indicator as to how well the model is representing the physical properties of the basin. We calculated and recorded the magnitude of the peak discharge and the time between the start of precipitation and the peak discharge for each storm event for the Flux-PIHM, API-Continuous and observational hydrographs. These calculations were made using surface flow only. With base flow removed, it was possible to conduct a concrete assessment of the ability of each model to capture the physical processes associated with peak flow and time to peak.

This study employs the Nash Sutcliffe model efficiency coefficient to further measure the accuracy of Flux-PIHM and API-Continuous in relation to the observations. The Nash Sutcliffe coefficient is shown in equation 1

$$E = 1 - \frac{\sum_{t=1}^{T} \left(Q_o^t - Q_m^t\right)^2}{\sum_{t=1}^{T} \left(Q_o^t - \overline{Q_o}\right)^2} \qquad (1)$$

where Q_o is the observed discharge and Q_m is the modeled discharge (Nash & Sutcliffe, 1970). Values can range from $-\infty$ to 1, with 1 corresponding to an exact fit and negative values indicating that the mean of the observed discharge is a better predictor than the model. For further commentary on the Nash Sutcliffe coefficient and a discussion of its biases, the reader is referred to Krause et al., (2005). Nash-Sutcliffe coefficients were calculated between Flux-PIHM and observations and API-Continuous and observations for discharge for the entirety of 2010.

As described previously, for each modeled and observed hydrograph, base flow was removed to produce a profile of runoff for each storm event. The area under the curve of each runoff-only hydrograph was calculated using the trapezoidal rule to estimate the integral, which is equivalent to the volume of total runoff. The volume was divided by the total area of the basin to calculate depths of total runoff (m). Using these values, we assessed the ability of each model to accurately simulate the total amount of runoff for a given storm event. The ability for Flux-PIHM and API-Continuous to accurately predict total runoff is an indicator as to how well the model represents the soil moisture of the basin and the physical properties related to it.

2.6 Precipitation Analysis

We assessed whether differences in precipitation forcing datasets for the same region exist and if so, whether these differences translate into differences in discharge output between models. For this comparison, we use the Noah LSM produced precipitation dataset from NLDAS-2, the mean areal precipitation dataset which was used as forcing for API-Continuous and precipitation observations measured by a distrometer located in the nearby Shale Hills Critical Zone Observatory (http://www.czo.psu.edu/data_time_series.html). This selection of datasets showcases the variety of precipitation forcing that can be used for a model in an operational forecasting setting. The first dataset is extracted from a national data assimilation system, the second dataset uses a spatial sampling of local rain gauge measurements combined with radar reflectivity precipitation estimates and the third dataset uses direct observations from a distrometer with high temporal resolution, yet is located slightly outside of the Little Juniata River basin and does not capture the spatial heterogeneity of precipitation. The precipitation observations associated with each of our twelve storm events were extracted from the datasets. The time series were compared with respect to the duration of the precipitation event, the rate at which precipitation fell per hour, and the total amount of precipitation recorded for the given event.

Chapter 3

Results

We conducted various analyses to compare the river forecasting performance of the Flux-PIHM and API-Continuous models to observations for the year 2010 at the Spruce Creek gauge in the Little Juniata River Basin. Figure 3.1 displays the hydrographs for the entirety of 2010 for both models and observations.

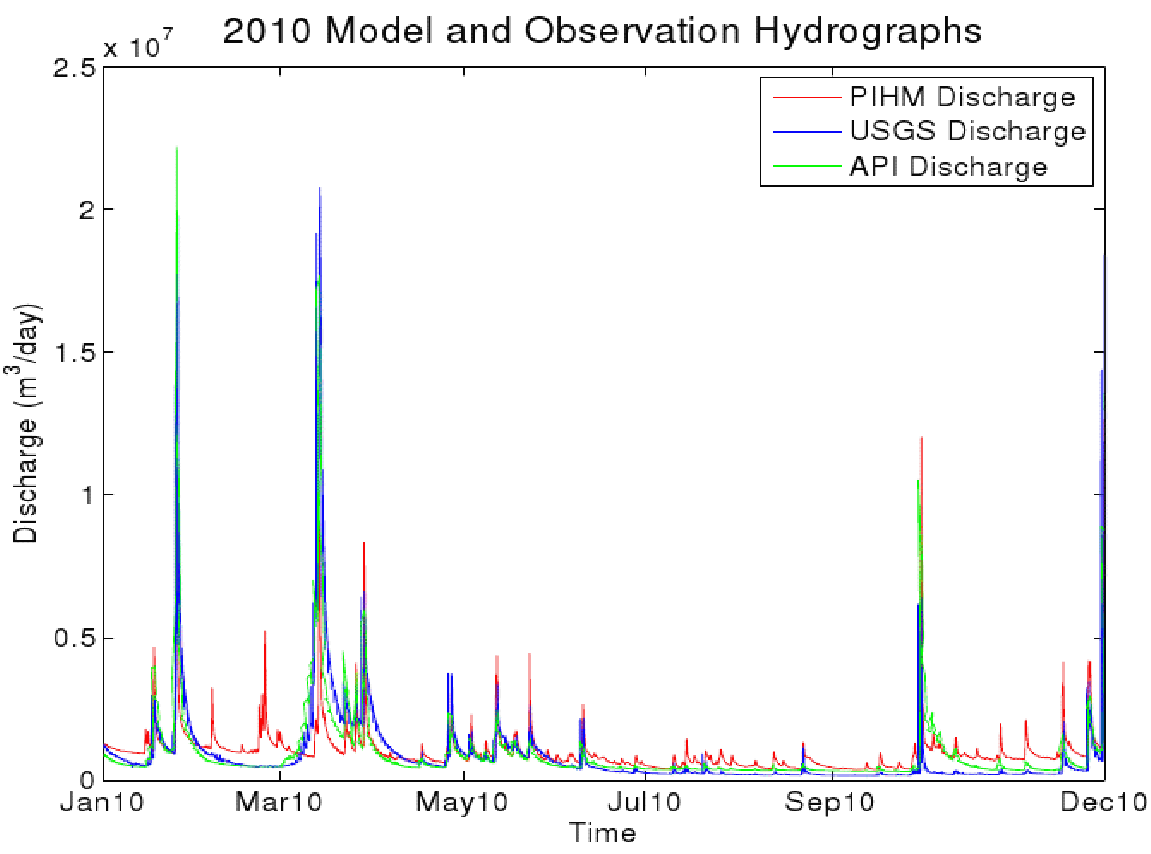
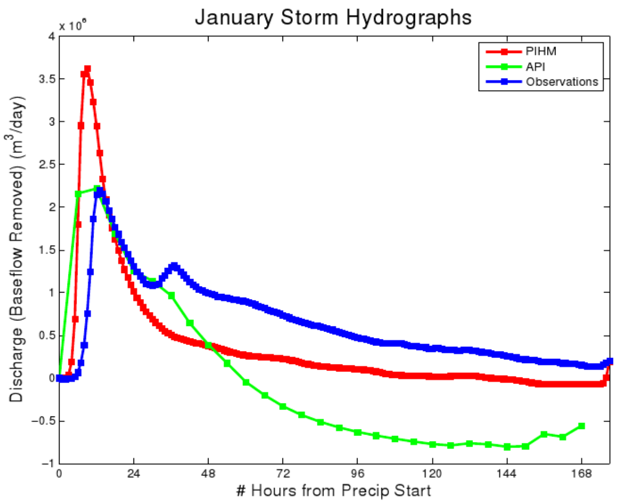
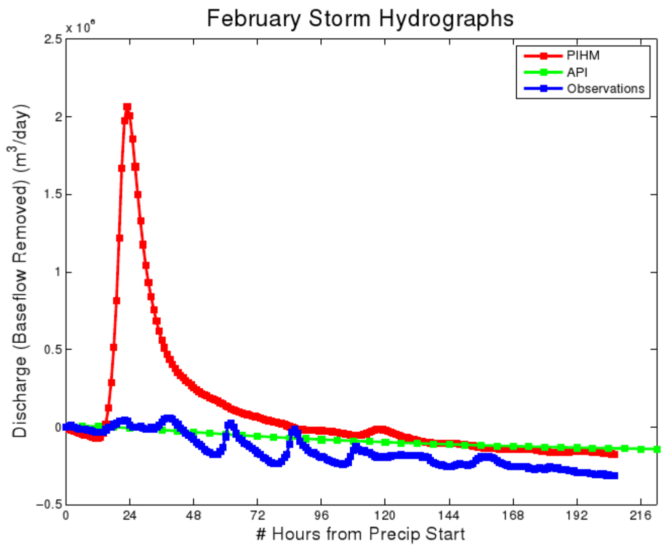
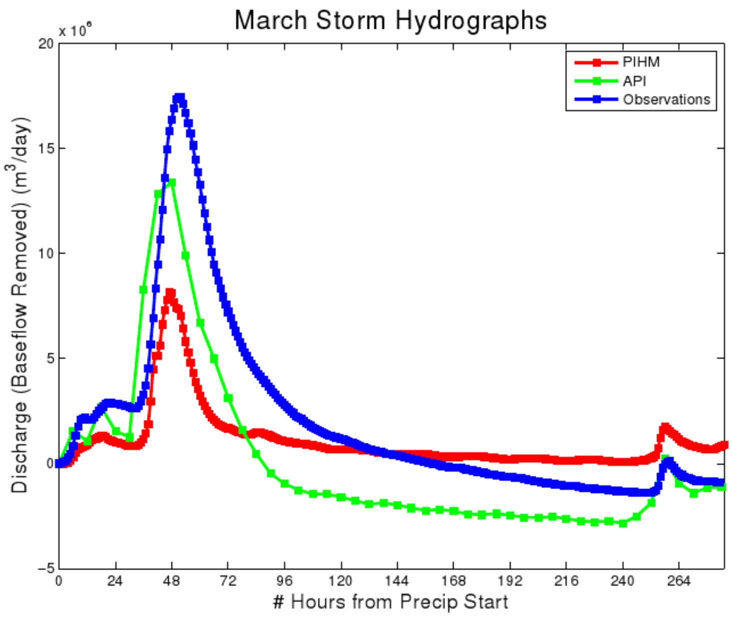


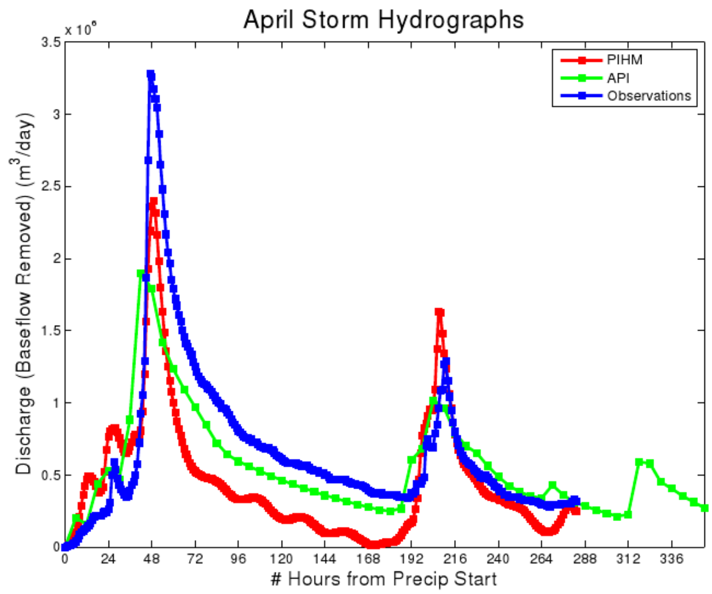
Figure 3.1. Flux-PIHM (red), API-Continuous (green) and USGS Observation (blue) hydrographs for the entirety of 2010. Discharge in units of m^3/day.

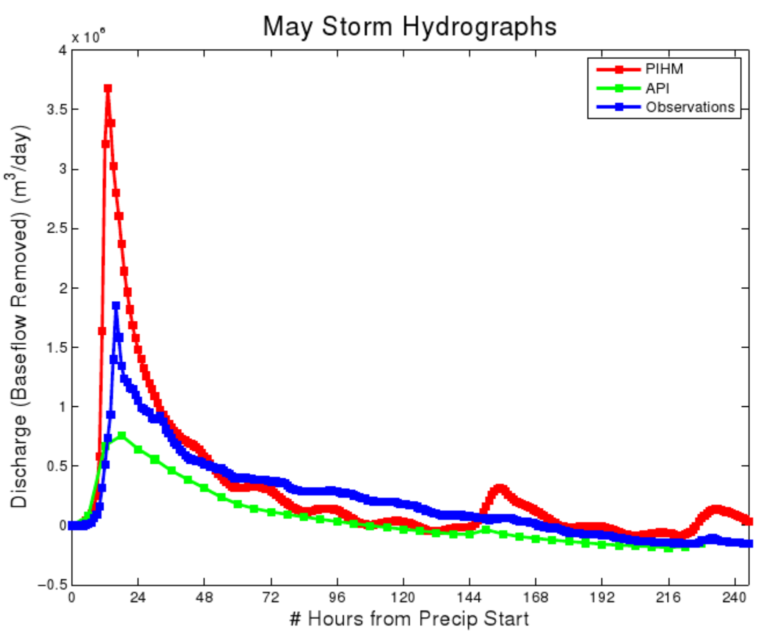
During the winter months and beginning of spring, the base flow as modeled by Flux-PIHM is higher than API-Continuous output and observations. Flux-PIHM also tends to overestimate the peaks in discharge during this time period. In early March, Flux-PIHM simulates discharge peaks that are not observed or modeled by API-Continuous at all. Models and observations are in best agreement in May. For the entirety of 2010, Flux-PIHM compared to observations has a Nash Sutcliffe coefficient of .53, while the value for API-Continuous compared to observations is .87, indicating that API-Continuous is, on average, a better simulator of discharge. However, model performance on a case-by-case basis is a more relevant concern than annually averaged performance. Figure 3.2 displays the hydrographs, plots of discharge versus time, with base flow removed for each of the 12 storm events. Based on our methodology for removing base flow, a value of negative discharge indicates that the discharge magnitude fell below the storm's initial value.

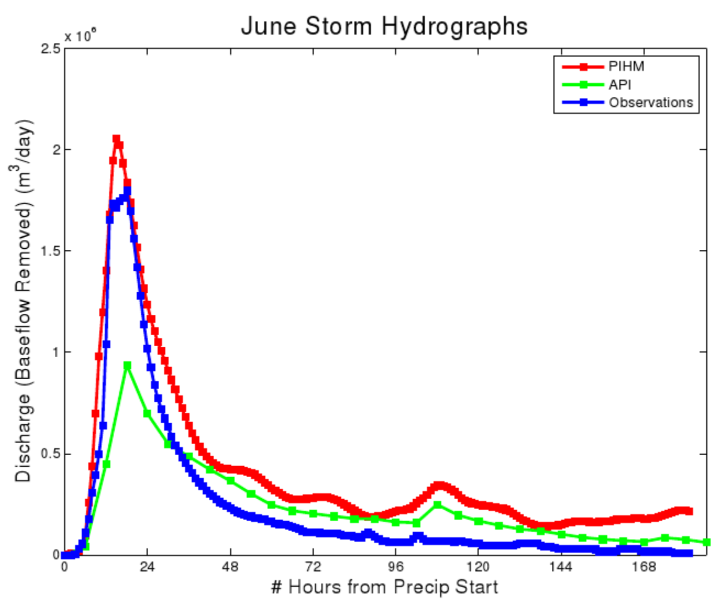


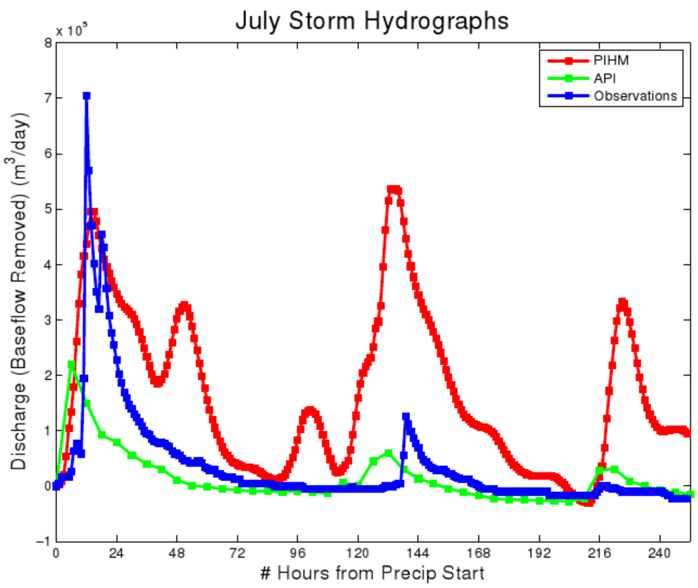


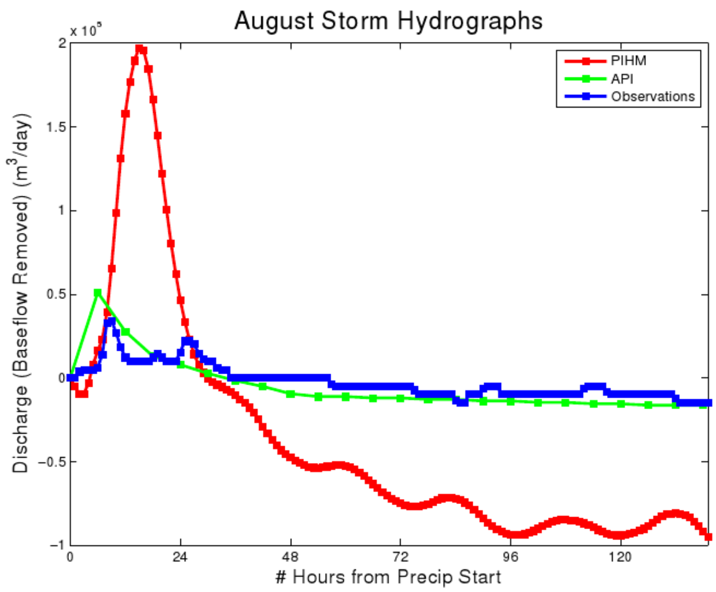

March Storm Hydrographs
PIHM
API
Observations
Discharge (Baseflow Removed) (m^3/day)
x 10^6
Hours from Precip Start

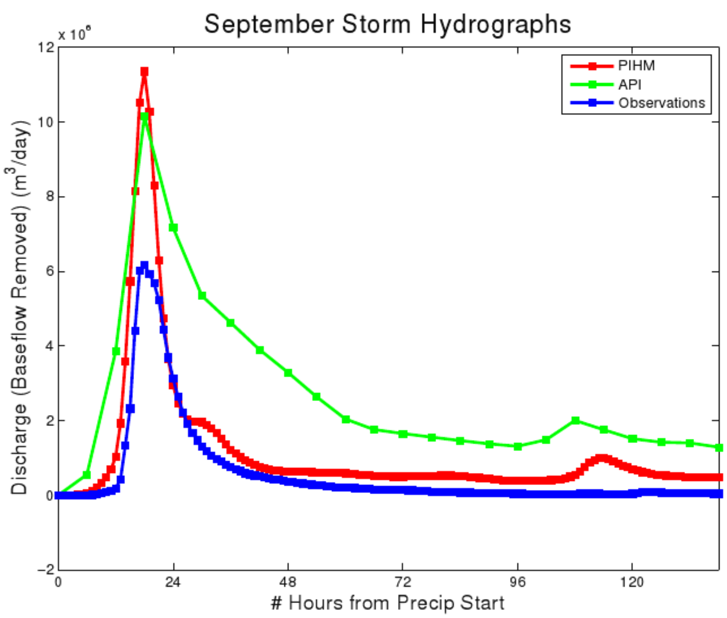

April Storm Hydrographs
PIHM
API
Observations
Discharge (Baseflow Removed) (m^3/day)
x 10^6
Hours from Precip Start

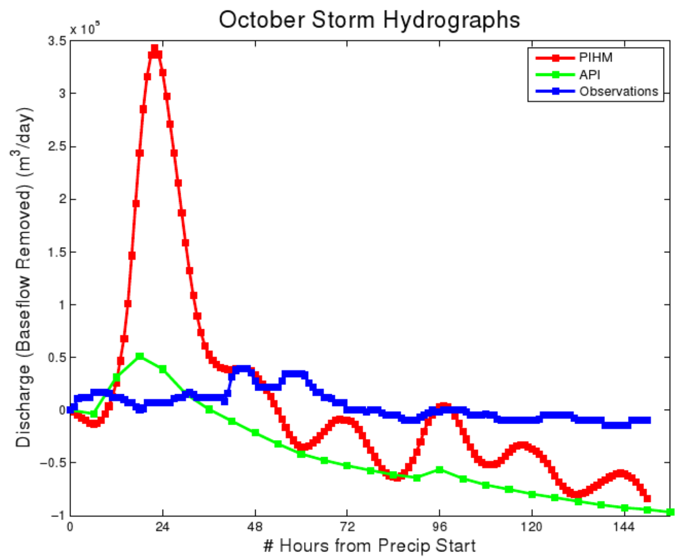

May Storm Hydrographs
PIHM
API
Observations
Discharge (Baseflow Removed) (m^3/day)
x 10^6
Hours from Precip Start


June Storm Hydrographs
PIHM
API
Observations
Discharge (Baseflow Removed) (m^3/day)
x 10^6
Hours from Precip Start


July Storm Hydrographs
PIHM
API
Observations
Discharge (Baseflow Removed) (m³/day)
Hours from Precip Start


August Storm Hydrographs
PIHM
API
Observations
Discharge (Baseflow Removed) (m³/day)
Hours from Precip Start


September Storm Hydrographs
PIHM
API
Observations
Discharge (Baseflow Removed) (m³/day)
Hours from Precip Start


October Storm Hydrographs
PIHM
API
Observations
Discharge (Baseflow Removed) (m³/day)
Hours from Precip Start

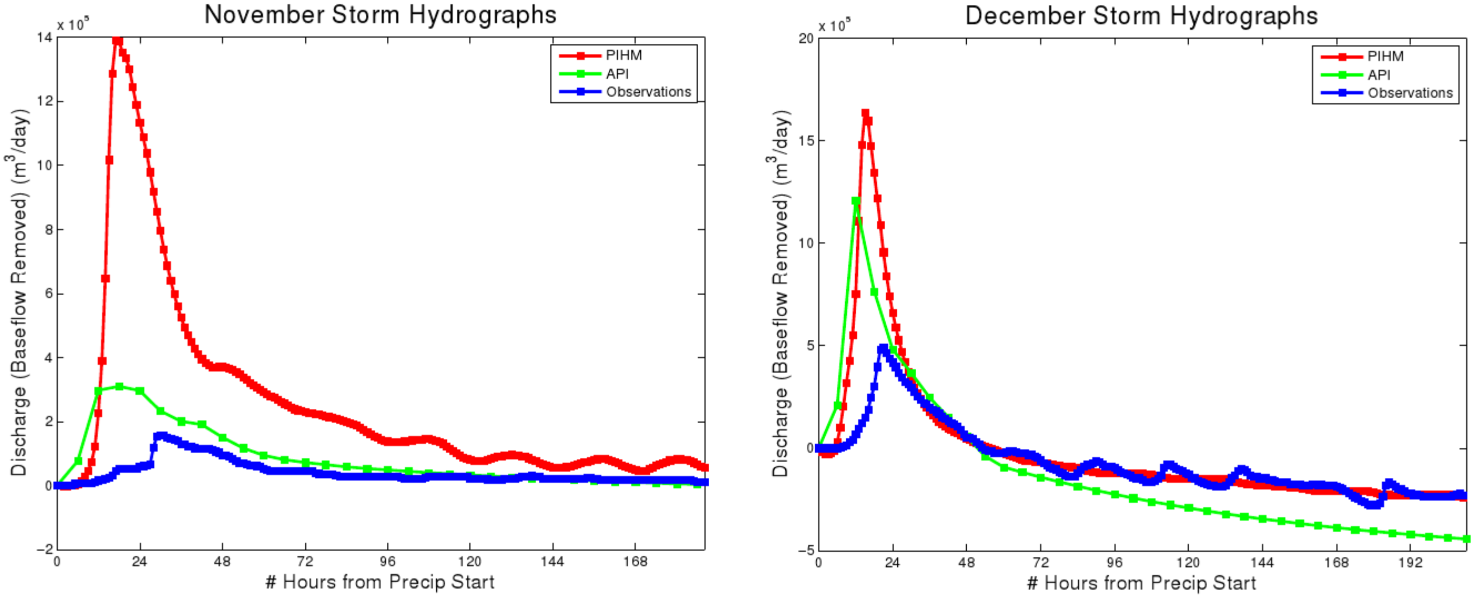
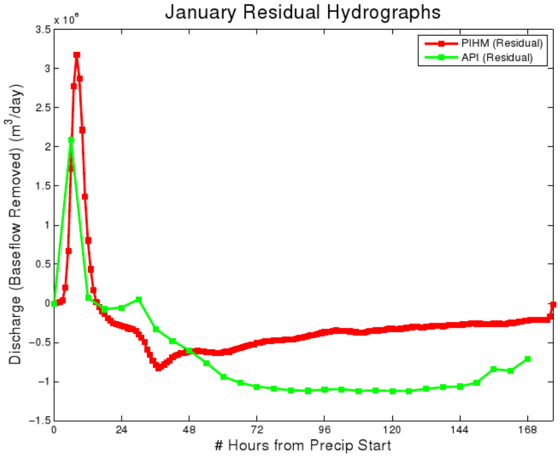
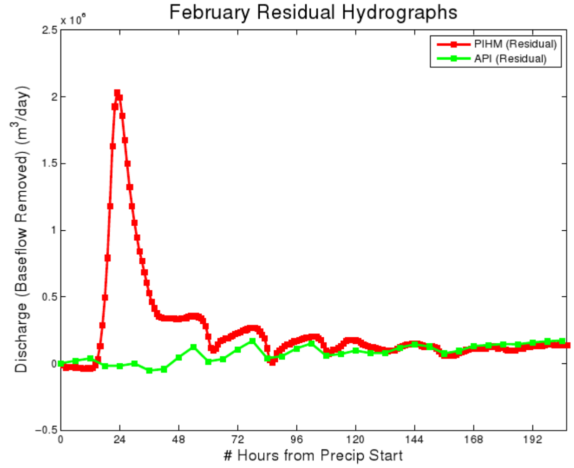


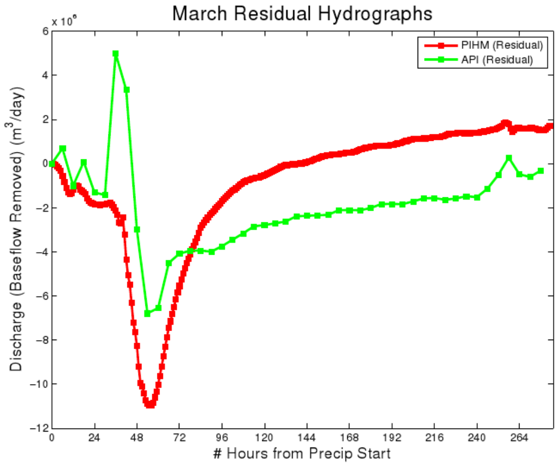
Figure 3.2. Flux-PIHM (red), API-Continuous (green) and USGS observation (blue) discharge hydrographs minus base flow for the each of the 12 storm events. One storm event per month in 2010. A negative discharge value indicates the discharge magnitude is less than the initial base flow value. Note discharge in m^3/day and scale is not uniform.

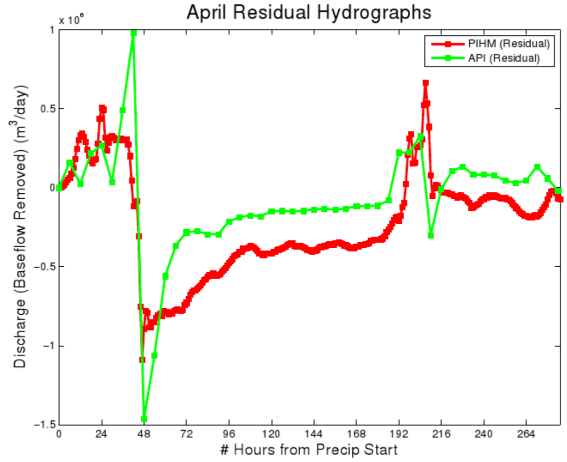
Most of these cases follow a pattern typical of storm event hydrographs. Responding to the precipitation, discharge rises (*rising limb* of the hydrograph) to a peak and returns to near base flow values along the section of the hydrograph termed the *recession curve*. Secondary peaks within the hydrographs displayed are a result of succeeding, smaller precipitation events. The diurnal cycle of melting snow can be observed in the tail end of the December hydrograph. Although API-Continuous output has a coarser temporal resolution than Flux-PIHM, that disparity alone does not lead to a noticeable difference between the Flux-PIHM and API-Continuous profiles. Figure 3.3

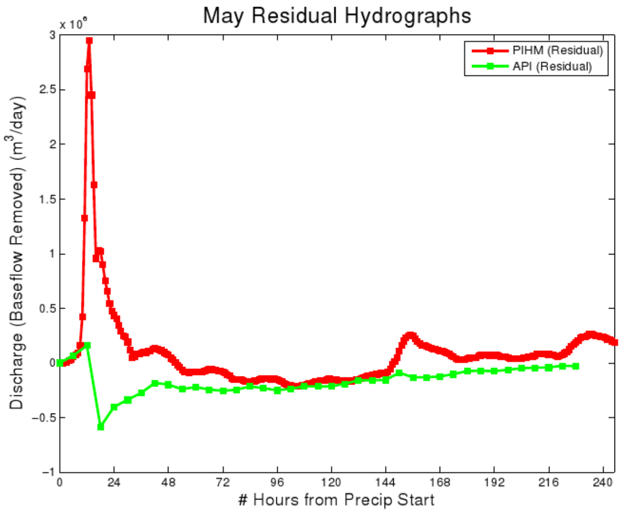
consists of residual hydrographs for each storm, produced by subtracting the model output from respective observations to display model error.

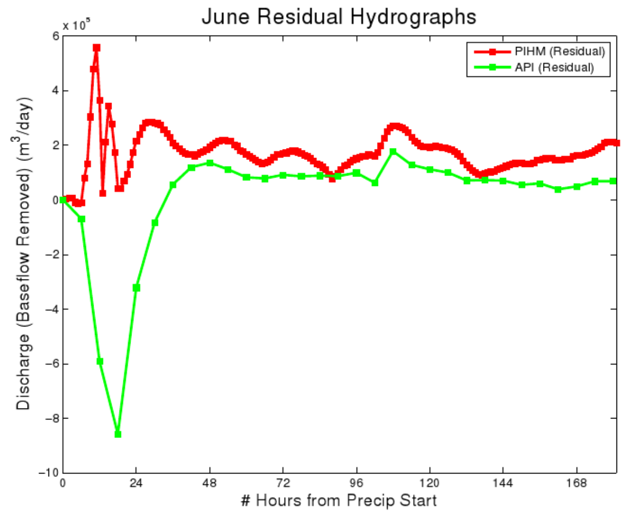


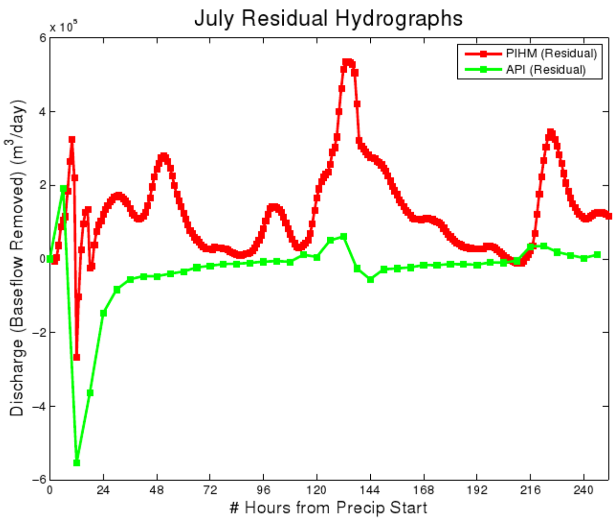


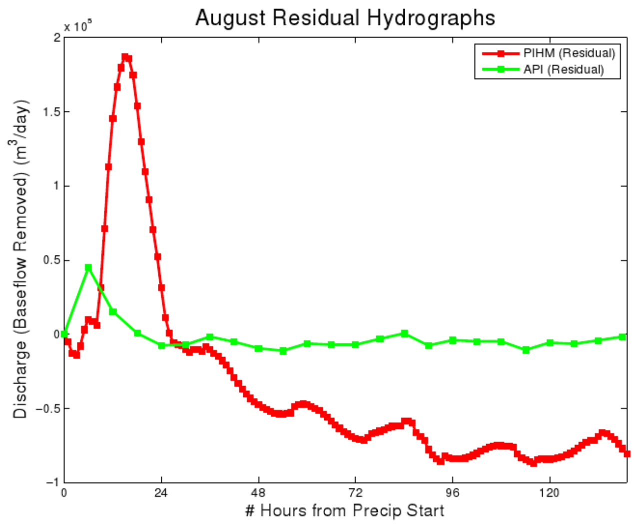


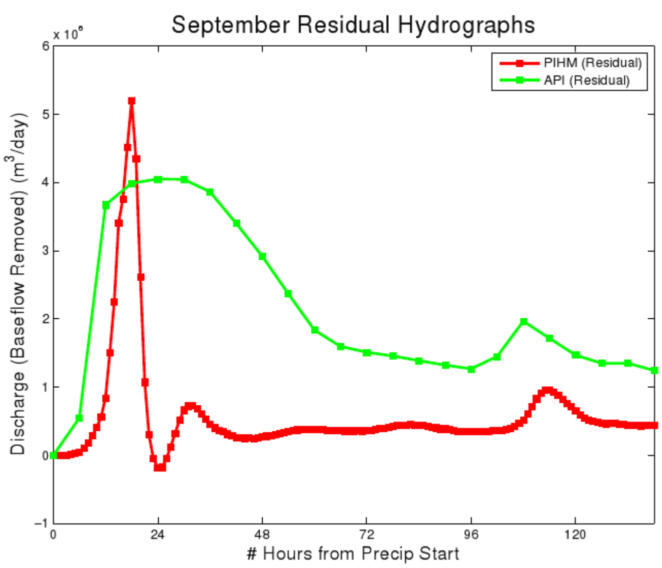


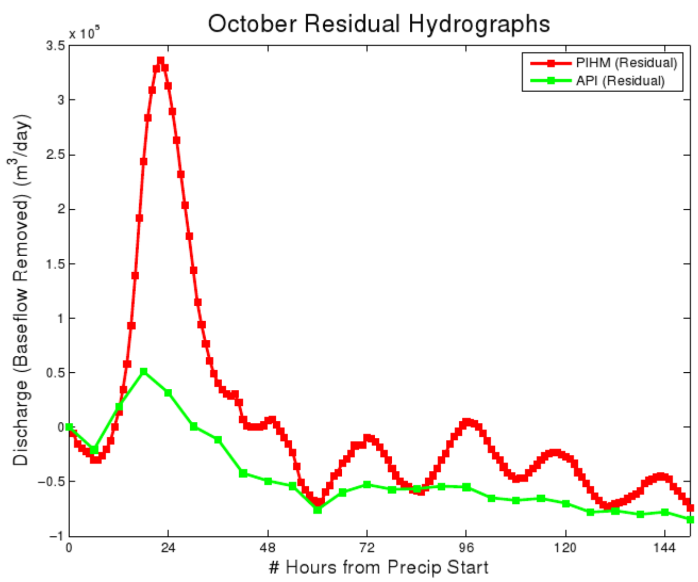





July Residual Hydrographs
x 10^5
PIHM (Residual)
API (Residual)
Discharge (Baseflow Removed) (m^3/day)
Hours from Precip Start


August Residual Hydrographs
x 10^5
PIHM (Residual)
API (Residual)
Discharge (Baseflow Removed) (m^3/day)
Hours from Precip Start


September Residual Hydrographs
x 10^6
PIHM (Residual)
API (Residual)
Discharge (Baseflow Removed) (m^3/day)
Hours from Precip Start


October Residual Hydrographs
x 10^5
PIHM (Residual)
API (Residual)
Discharge (Baseflow Removed) (m^3/day)
Hours from Precip Start

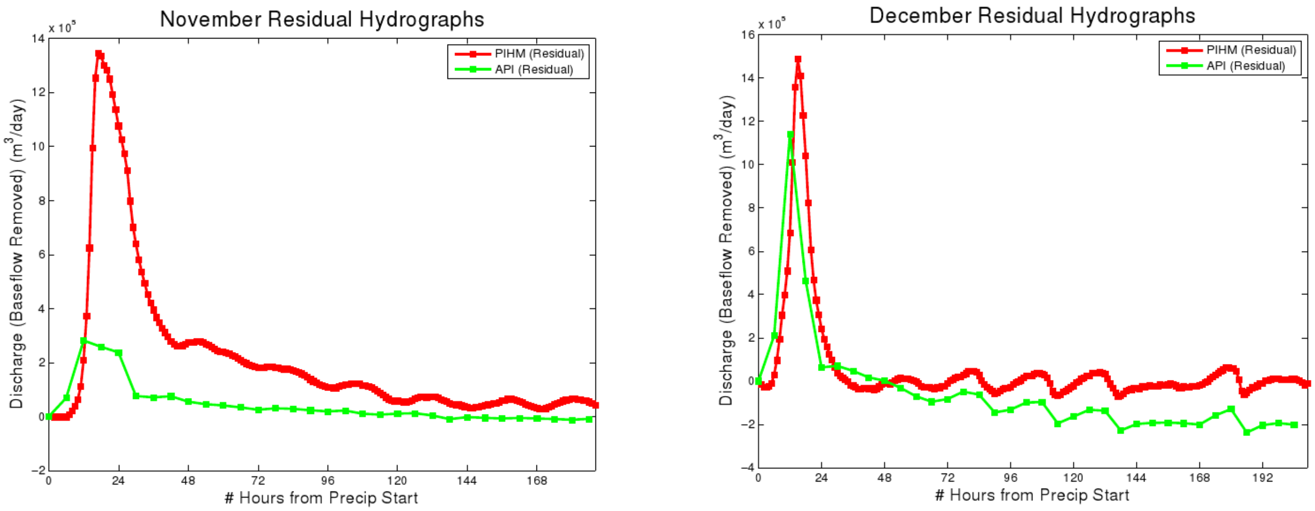


Figure 3.3. Flux-PIHM (red), API-Continuous (green) and USGS observation (blue) residual hydrographs minus base flow for the each of the 12 storm events. One storm event per month in 2010. A negative (positive) value indicates model discharge value was less than (greater than) the respective observation. Note discharge in m^3/day and scale is not uniform.

As evident in the residual hydrographs, the error between API-Continuous and observations generally increases towards the end of the hydrograph compared to the start of the event. Such a trend is apparent in the January, March and December residual hydrographs.

Figure 3.4a,b contains two scatter plots comparing the modeled and observed peak discharge magnitude for each storm event without base flow. Figure 3.4a contains all storm events and 3.4b is a zoomed in version of the same data but with the largest two storms removed for easier visualization. The events have been identified by the meteorological season in which they occurred.

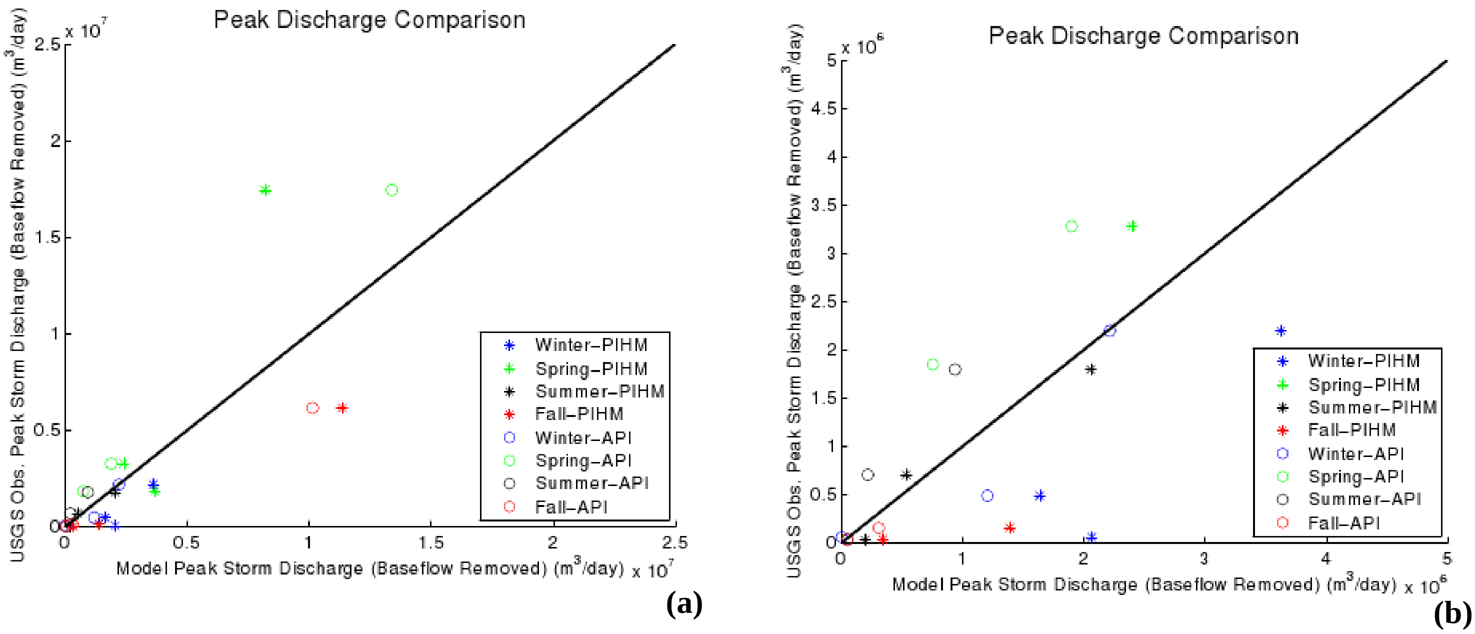


Figure 3.4. Comparison of the magnitude of peak discharge per a) each storm event and b) all but the two largest storm events as estimated by Flux-PIHM, API-Continuous versus observations. Events are grouped based on meteorological season in which it occurred. Diagonal line represents the 1:1 ratio. Base flow was removed from discharge values, which are in m^3/day.

A marker on the diagonal 1:1 ratio line indicates that the peak discharge as modeled by Flux-PIHM or API-Continuous is identical to the observed peak discharge for a given event. Our results indicate that Flux-PIHM overestimates the peak discharge amount in most of the storm events. The same conclusion is apparent in the positive Flux-PIHM errors seen in many of the Figure 3.3 residual hydrographs. Although Flux-PIHM was optimized using two large discharge events, API-Continuous is the more accurate model for the simulation of peak discharge in the larger spring and fall events. In agreement with the conclusions drawn from Figure 3.2, API-Continuous consistently simulated peak discharge magnitude more accurately than Flux-PIHM in the winter months. Furthermore, Flux-PIHM simulates peak discharge more accurately than API-Continuous in the summer cases.

Figure 3.5 shows a comparison of the elapsed time between start of the precipitation event and the occurrence of the peak in discharge. The model output is again identified by model and the meteorological season during which the storm occurred.

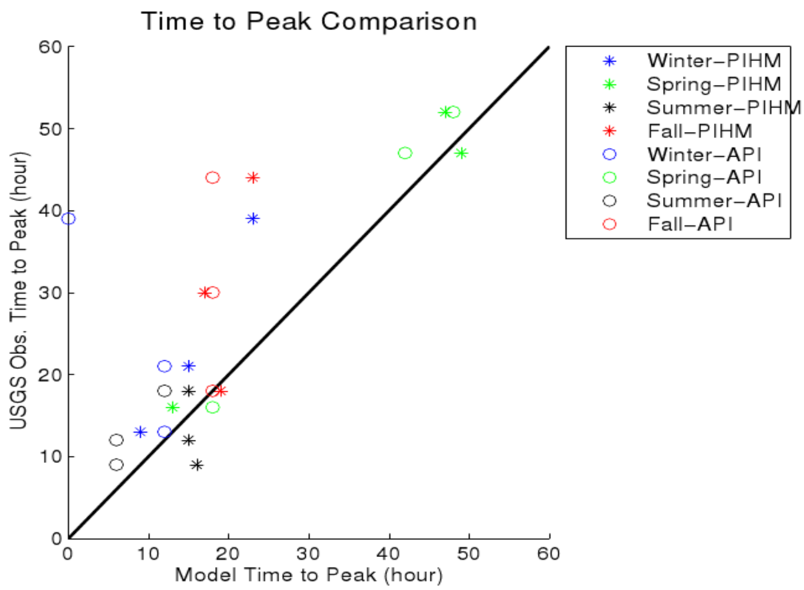


Figure 3.5. Comparison of the time (hours) between the start of precipitation and the peak of the discharge per storm event as estimated by Flux-PIHM, API-Continuous and as observed. Events are grouped based on meteorological season in which it occurred.

Both API-Continuous and Flux-PIHM underestimate the time between the start of precipitation and the peak of the discharge for most of the storm events. The models are simulating a peak in discharge faster than what was actually observed. The models are in closest agreement during the fall, and no trend indicates a degradation or improvement in model performance for longer duration events.

We calculated the total runoff for each storm event as observed and modeled by Flux-PIHM and API-Continuous. Figure 3.6 shows a comparison of these calculations.

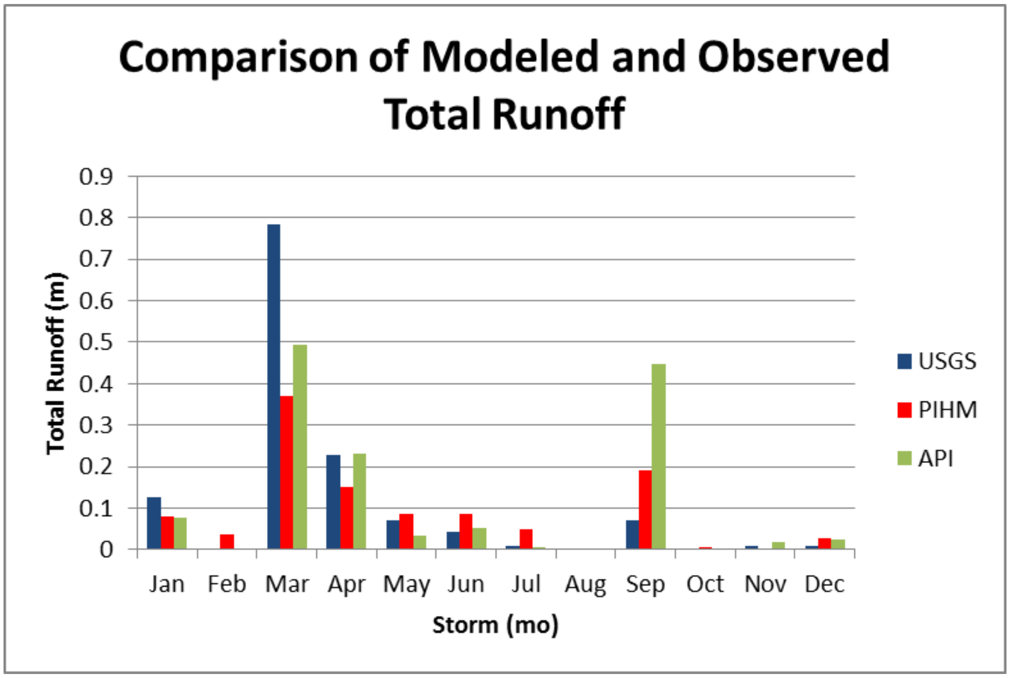


Figure 3.6. Total runoff (m) for each storm event as estimated by Flux-PIHM (red), API-Continuous (green) and as observed (blue).

Flux-PIHM tends to underestimate total runoff in the earlier months of the year, especially in the spring, and tends to overestimate total runoff in the summer and fall months. Results for the March, April and September storms suggest that API-Continuous simulates more total runoff than Flux-PIHM for large discharge events. An analysis of the corresponding hydrographs for these storms indicates that API-Continuous simulated a higher discharge peak than Flux-PIHM for the March storm, leading to a higher total runoff, yet the API-Continuous peak discharge was less than the Flux-PIHM value for the April and September storm. Instead, the higher total API-Continuous simulated runoff values for these storms was a result of a wider peak of increased discharge, indicating API-Continuous simulated a faster rise and fall in discharge magnitude. In multiple events, including the April and September storm, Flux-PIHM simulates a shorter duration of increased flow than API-Continuous does.

We compared multiple precipitation datasets to determine whether differences in precipitation magnitude and duration existed, and whether these differences could cause model inconsistencies if these datasets were used interchangeably for model forcing. We compared the total precipitation and duration of precipitation for each storm event as observed by the NLDAS-2 forcing used for Flux-PIHM, the mean areal precipitation used for API-Continuous and observations from a distrometer located at the Shale Hills Observatory. Table 3.1 displays the mean, standard deviation and standard error of total precipitation and duration for the 12 storm events.

	NLDAS-2 Event Total Precip. (m)	**API-Continuous Forcing** Event Total Precip. (m)	**Shale Hills Distrometer** Event Total Precip. (m)		**NLDAS-2** Event Precip. Duration (hrs)	**API-Continuos** Event Precip. Duration (hrs)	**Shale Hills Distrometer** Event Precip. Duration (hrs)
Mean	$6.21(10)^{-4}$	$2.65(10)^{-2}$	$2.33(10)^{-2}$		22.8	22.5	20.3
Standard Dev.	$6.17(10)^{-4}$	$2.72(10)^{-2}$	$2.34(10)^{-2}$		16.0	18.3	19.3
Standard Error	$1.78(10)^{-4}$	$7.84(10)^{-3}$	$7.41(10)^{-3}$		4.63	5.28	6.11

Table 3.1. The mean, standard deviation and standard error of the total precipitation and duration of precipitation of the 12 storm events as observed by the NLDAS-2 forcing data, the mean areal precipitation data used to force API-Continuous and a distrometer located in the Shale Hills Observatory.

A significant difference in total precipitation does exist between the three datasets. Total precipitation is considerably less in the NLDAS-2 dataset then the API-Continuous forcing and the distrometer. This disagreement has been highlighted in previous studies. Luo, et al., (2003) explains that NLDAS-2 uses daily precipitation as a base and interpolates to hourly observations. The dataset is further smoothed because it incorporates observations from many point measurements, the majority of which may not have observed precipitation. No significant difference in precipitation duration exists between the three datasets.

Chapter 4

Discussion

Due to logistical and time constraints, the investigators in this study did not have full access to both models to definitively confirm or reject theories that may serve as causation to the results described above, but here we offer insight into possible explanations to the identified trends that could be tested in additional studies.

We determined that Flux-PIHM overestimates base flow in the winter and early spring events. Flux-PIHM has insufficient snow physics built into the model thereby allowing too much base flow to be simulated during these months. In the early spring months, Flux-PIHM simulations may include more melting than is actually occurring. Improving snow physics, or calibrating the model with temperature data, which directly affects surface melting processes, may help to reduce the base flow error during these months. Throughout the year, including winter and early spring, Flux-PIHM overestimated the peak discharge magnitude of most of the storm events. Since PIHM was calibrated with large discharge events, Flux-PIHM may have a wet bias. This bias may lead to simulated peak discharge values that are greater than observations. Additionally, Flux-PIHM simulations may include an underestimation of evapotranspiration which would subsequently allow for more water from precipitation to contribute to discharge. A comparison of Flux-PIHM estimates of evapotranspiration with other datasets may offer more clarity.

Based on the storm events studied, Flux-PIHM simulates peak discharge more accurately than API-Continuous in the summer months. As a distributed model, Flux-

PIHM accounts for the spatial variability across the basin, while API-Continuous does not have this capability. In the summer time, storms are more likely to be smaller scale, convective events, instead of widespread, synoptic systems. The distribution of precipitation across the basin may not be uniform for a summertime convective storm, which will inevitably affect the duration and magnitude of the responding discharge increase. A well calibrated distributed model may offer an advantage in mesoscale precipitation scenarios over a lumped model.

In multiple events analyzed in this study, the error in discharge modeled by API-Continuous compared to observations increased towards the end of the hydrograph as discharge returned to base flow conditions. API-Continuous may not be properly accounting for soil moisture conditions. For example, if API-Continuous simulates conditions that are too moist, more water from precipitation will be available to contribute to runoff, further increasing the discharge above base flow values. API-Continuous may struggle to accurately represent soil moisture after high flow conditions. In an operational setting, however, a forecaster can hand tune the model, adjusting the model so the simulated hydrograph more closely matches observations.

Figure 3.5 illustrated that both models generally simulate a shorter elapsed time between the start of a precipitation event and the peak of the discharge than is actually observed. One factor for this trend may be that the models are incorrectly distributing the precipitation between the base flow and surface flow components of the discharge. Base flow propagates through the basin at a slower time scale than surface flow. If the proportion of surface flow to base flow is higher than observations, the model output may simulate the discharge peak too quickly.

The assessment of total runoff of each storm event indicates that Flux-PIHM underestimates total runoff in the early months of the year, especially in early spring, and overestimates total runoff in the summer and early fall. This systematic bias could be addressed with improved tuning of the model. API-Continuous simulates more total runoff than Flux-PIHM for events of high runoff magnitude, including the March, April and September storms. The hydrographs for these storms found in Figure 3.2 illustrates that a high API-Continuous peak discharge value caused the higher total runoff value in the March storm. However, the API-Continuous peak discharge values were smaller than the corresponding Flux-PIHM peak discharge values for the April and September storms. Instead, the ridge in the API-Continuous hydrographs was wider than the corresponding Flux-PIHM ridges for those storms, leading to more "area under the curve". Flux-PIHM progresses through the process of increasing and decreasing discharge slower than API-Continuous does for these precipitation events. This notion of a shorter, yet wider API-Continuous discharge curve compared to the Flux-PIHM output also occurs in the January storm. Accurate simulation of the peak discharge value may alone not lead to an accurate simulation of total runoff. A model may also need to be tuned to account for the duration of non-base flow, increased discharge values for a storm event.

Many of the trends and possible causes of the trends can be addressed with improved, or more focused, calibration of the models. The river forecasting performance of both Flux-PIHM and API-Continuous relies on various parameters that can be tuned to maximize the accuracy of one or more of the measures discussed. PIHM was only calibrated with discharge for this study, but groundwater, heat fluxes, temperature and other variables could be factored into the calibration process to address some of the errors highlighted in this study. Although the NLDAS-2 precipitation forcing was significantly less in magnitude than the forcing data used for API-Continuous, Flux-PIHM discharge output was not proportionally less than API-Continuous output, promoting the notion that calibration of the model plays an important role in model accuracy from a river forecasting perspective.

Chapter 5

Conclusions

We assessed the river forecasting performance of the distributed, physically based Flux-PIHM model and the lumped, conceptual API-Continuous model compared to USGS stream flow observations for 2010 at the Spruce Creek stream flow gauge in the Little Juniata River Basin. We specifically investigated 12 storm events during 2010. We analyzed the hydrographs for the entirety of 2010 as modeled and observed, assessing the accuracy of the Flux-PIHM and API-Continuous simulations. On a storm-by-storm basis we compared model output and observations in relation to the peak discharge magnitude of the event, the elapsed time between the start of precipitation and the peak discharge and the total runoff. The results highlighted the benefits of distributed or lumped models in a river forecasting setting. We determined possible causes for the results observed, many of which point to calibration and parameterization improvements that could be made within the models. For example, Flux-PIHM overestimates base flow and peak discharge in the winter and early spring months due to poor snow physics representation in the model. API-Continuous tends to simulate peak discharge less accurately in the summer months than Flux-PIHM because it cannot account for the spatial variability of precipitation associated with mesoscale, convective events that commonly occur during time of year.

We hope to further this study by including more storm events in the analysis. Robust conclusions are difficult to draw with only 12 subjectively chosen events, or only

3 events per season. Data availability was limited to 2010 but with more years, more events could feasibly be chosen. We would also like to further explore the effects of using different forcing data on the models. We compared the two precipitation forcing datasets and a local point observation dataset, but since we could not force API-Continuous with any other precipitation datasets besides the mean areal precipitation that was used for the model, we could not necessarily quantify the effects that the difference in the precipitation datasets could have on model output. Comparing Flux-PIHM to the conceptual Sacramento-Soil Moisture Accounting Model (SAC-SMA) (Burnash et al., 1973; Burnash et al., 1995) may also allow for more flexibility in our analysis. SAC-SMA is heavily used at National Weather Service River Forecasting Centers nationwide and unlike API-Continuous the model can be executed outside of a River Forecast Center in a research setting. Completing our analyses at multiple basins may also yield results worthy of analysis.

We hope this work spurs further study into the performance of distributed and conceptual models as river forecasting tools. Previous work has assessed the accuracy of each type of model with respect to relevant river forecasting characteristics such as peak discharge magnitude or time to peak discharge, but we feel that few of these studies have been able to sufficiently pinpoint the causes of the noted trends. As the field of hydrologic modeling progresses the proper question is not which type of model is more accurate, but rather what factors lead to accuracy in a certain model, and under which hydrologic conditions may a certain model be preferable.

REFERENCES

Beschta, R. 1990. Peakflow estimation using an antecedent precipitation index (API) model in tropical environments. *IN: Research Needs and Applications to Reduce Erosion and Sedimentation in Tropical Steeplands.IAHS Publication no.192.International Association of Hydrological Sciences, Washington, DC.1990.p 128-137.3 Fig, 1 Tab, 10 Ref*

Beven, K. 1989. Changing ideas in hydrology ~ The case of physically-based models. J, Hydrol.,105:157-172

Burnash, R.J.C. 1995. The NWS river forecast system – catchment modeling. In: Singh, V.P. (Ed.), Computer Models of Watershed Hydrology. Water Resources Publications, Littleton, Colorado, pp. 311–366.

Burnash,R.J.C.,Ferral, R.L.,McGuire,R.A.1973.AGeneralizedStreamflow Simulation System Conceptual Model for Digital Computers. US Department of Commerce National Weather Service and State of California Department of Water

Capracasa, J.M. 2005. Decision rational total maximum daily loads Little Juniata River Watershed for nutrients and sediments Blair County, Pennsylvania. United State Environmental Protection Agency: Region III

Clarke, R. T. 2008. Issues of experimental design for comparing the performance of hydrologic models, Water Resour. Res., 44, W01409

Continuous API Model. 2002. National Weather Service: Hydrologic Research Laboratory.

Ek, M. B., K. Mitchell, Y. Lin, E. Rogers, P. Grummann, V. Koren, G. Gayno and J. Tarpley. 2003. Implementation of Noah land surface model advances in the National Centers for Environmental Prediction operational Mesoscale Eta Model. J. Geophys. Res., 108, 8851

Hansen, N., 2006. The CMA evolution strategy: a comparing review. Towards a new evolutionary computation 75-102.

Hansen, N., and Ostermeier, A. 2001. Completely derandomized self-adaptation in evolution strategies. Evolutionary Computation 9: 159–195.

Kampf, S. 2006. Towards Improved Representations of Hydrologic Processes: Linking Integrated and Distributed Hydrologic Measurements to a Physically-Based Model for a Planar Hillslope Plot. Water Resources Series, No. 183

Krause, P., Boyle, D.P., Bäse, F. 2005. Comparison of different efficiency criteria for hydrological model assessment. Advances in Geosciences 5, 89–97.

Luo, L., Robock, A., Mitchell, K.E., Houser, P.R., Wood, E.F., Schaake, J.C., Lohmann, D., Cosgrove, B.A., Wen, F., Sheffield, J., Duan, Q., Higgins, R.W., Pinker, R.T., and Tarpley, J.D., 2003. Validation of the North American Land Data Assimilation System (NLDAS) retrospective forcing over the southern Great Plains, J. Geophys. Res., 108(D22), 8843.

Mitchell, K. E., et al. 2004. The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system, J. Geophys. Res., 109, D07S90.

Moradkhani, H., Sorooshian, S., 2008. General review of rainfall-runoff modeling: model calibration, data assimilation, and uncertainty analysis. In: Sorooshian, S. et al. (Eds.), Hydrological Modelling and the Water Cycle – Coupling the Atmospheric and Hydrological Models. Springer, Berlin

Nash, J. E. and Sutcliffe, J. V. 1970. River flow forecasting through conceptual models, Part I - A discussion of principles, J. Hydrol., 10, 282–290.

Qu, Y., and Duffy, C.J. 2007. A semidiscrete finite volume formulation for multiprocess watershed simulation, Water Resour. Res., 43, W08419

Reed, S.M., Koren, V., Smith, M., Zhang, Z., Moreda, F., Seo, D.-J., DMIP participants. 2004. Overall distributed model intercomparison project results. Journal of Hydrology 298(1–4), 27–60.

Shi, Y., Davis, K.J., Duffy, C.J., and Yu, X. 2013. Development of a coupled land surface hydrologic model and evaluation at a critical zone observatory. Journal of Hydrometeorology, conditionally accepted.

Sittner, W.T., Schauss, C.E., Monro, J.C., 1969. Continuous Hydrograph Synthesis with an API type hydrologic model. Water Resources Res, Vol. 5, No. 5, P 1007-1022.

Smith, M.B., Seo, D.-J., Koren, V.I., Reed, S., Zhang, Z., Duan, Q.-Y., Cong, S., Moreda, F., Anderson, R., 2004a. The Distributed Model Intercomparison Project (DMIP): Motivation and Experiment Design. J. Hydrol, 298(1–4), 4–26

Smith, M., Koren, V., Reed, S., Zhang, Z., Zhang, Y., Moreda, F., Cui, Z., Mizukami, N. Anderson, E. and Cosgrove, B.A., 2012a. The distributed model intercomparison project – Phase 2: Motivation and design of the Oklahoma experiments. J. Hydrol. 418-419, 3-16

Smith, M., Koren, V., Zhang, Z., Zhang, Y., Reed, S.M., Zhengtao, C., Moreda, F., Cosgrove, B.A., Mizukami, N., Anderson, E.A., DMIP 2 Paricipants. 2012b. Results of the DMIP 2 Oklahoma experiments, J. Hydrol, 418-419, 17-48

Solomatine, D. P., and A. Ostfeld (2008), Data-driven modelling: Some past experiences and new approaches, J. Hydroinformatics, 10(1), 3 – 22

Xia, Y., Mitchell, K.E., Ek, M.B., Cosgrove, B., Sheffield, J., Luo, L., Alonge, C.J., Helin, W., Meng, J., Livneh, B., Duan, Q., Lohrmann, D. 2012. Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products, J. Geophys. Res., 117, D03109.

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Kramer, R., Alsheimer, F., Wind gust climatology for southern South Carolina and coastal northeast Georgia, *2012 NOAA Office of Ed. Science and Education Symposium,* August 2012

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