A STUDY IN COMPLEXITY OF DISTRIBUTED HYDROLOGY MODELS: S.W.A.T. VERSUS A PARAMETER EFFICIENT MODEL

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

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January 2013

ABSTRACT

The 2007 National Water Inventory report to Congress estimated that 45% of all streams and rivers in the US don't support their designated use. Of the possible causes of impairment, sediment and siltation are listed as the most common followed by pathogens, habitat alterations, metals and nutrients where agriculture is the leading source of impairment. Growing numbers of hydrologists have found that the majority of runoff and non-point source pollution come from small, saturated areas in the landscape. Some work has been done to model these areas but they do not perform significantly differently than models that do not incorporate this type of hydrology. Spatial distribution is seen to be an important aspect to modeling these areas well but has not proven to yield significantly different results. This study compares two variable source areas based models, a complex, distributed saturated areas model with a simple non-distributed model. Two watersheds were used for the study: Little Tonawanda Creek and Black Creek. Black Creek is listed as impaired on New York's official Clean Water Act 303(d) list. Little Tonawanda is located just west of Black Creek and is not listed as impaired. The Soil and Water Assessment Tool with modification to include saturated areas (SWAT-VSA) was chosen as the complex model and the Parameter Efficient Distributed (PED) model with shallow aquifers was used as the simple model. SWAT-VSA divides the watershed into topographic index (TI) classes that indicate the degree of soil saturation for each unit and PED uses a similar approach. Modeling snowmelt is an important component to simulating stream flow in regions that receive significant amounts of snow. Three modified snowmelt datasets were created and used to determine how snowmelt affected flow predictions. Both models with each snowmelt dataset were applied to both watersheds. Black Creek models yielded daily Nash Sutcliffe Efficiency (NSE) as high as 0.71 using the PED model and percent bias of -10.7%; a NSE of 0.62 and percent bias of -10.3% for Little Tonawanda Creek.. Validation periods using the PED model yielded higher NSE than calibrated years for Black and Little Tonawanda Creek. Based

on flow analysis from each TI class, SWAT would need internal modifications to attribute saturation-based interflow to higher TI classes thereby simulating VSA hydrology better. More representative delineation of TI classes for SWAT and better simulated snowmelt would improve predicted flows as well as simplify model parameterization. The snowmelt+adjusted dataset improved predictions during the calibration and validation time periods for both watersheds and models with the exception of the SWAT model for Black Creek. Although both models achieved similar metrics, PED requires less time, input data and fewer parameters making it more desirable given the goals of a project. It also predicted flows outside of the calibration period well making it more useful to simulate future scenarios.

ACKNOWLEDGEMENTS

To begin with, I would like to thank the United States Environmental Protection Agency and the New York Department of Environmental Conservation for providing funding for this project. I would like to thank Dr. Tammo Steenhuis, my advisor, for his guidance and patience throughout the project and for providing insight to the world of hydrologic modeling. I am indebted to Daniel Fuka and Steve Pacenka for helping with SWAT, calibrations, and answering many, many questions. Zach Easton was also able to provide valuable SWAT insight as well as calibration suggestions. I would also like to thank Margaret Philips at the United States Geological Survey for providing stream flow data that was not available via web interface.

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Introduction

The U.S. Environmental Protection Agency reported that 45% of all stream and rivers in the US don't support their designated uses. Another 4% are threatened to fall short of designated use (EPA ATTAINS). Of the possible causes of impairment, sediment and siltation are listed as the most common followed by pathogens, habitat alterations, metals and nutrients. Agriculture is reported as the leading source of impairment across the US and the Great Lakes, in particular (National Water Quality Inventory Report 2007). A growing number of hydrologists have demonstrated that a large portion of runoff and surface water pollution come from small, spatially distributed areas termed variable source areas (VSAs). Accurately identifying and modeling these areas would improve management decisions as best management practices could be better targeted to areas that are most likely to produce runoff and pollution.

Waters that do not meet water quality standards are required to have loading limits to restore the water body to a healthy state. These are called total maximum daily loads (TMDLs) and are defined after intensive study of watershed characteristics with a detailed model of the system. States will often use models to determine the effect of policy mechanisms on pollutant loadings to the watershed making them an important component to setting TMDLs and aiding decision-making (NRC 2001). They are becoming more important to forecasting future effects in light of climate change and its impact on water resources.

As the availability of forcing data for hydrologic models increases, the impetus to incorporate these data, especially with GIS tools, grows with the belief that models will become more reliable and robust. This is beneficial for TMDL development as decision-makers can better recommend and justify management practices and policies that will help mitigate pollutants. Unfortunately, large parameter sets and complex models can be cumbersome to calibrate as calibration procedures tend to parameterize the model with physically unrealistic values. This study seeks to simplify the modeling process to essential elements for understanding and mitigating runoff for TMDL development.

Background

VSA Hydrology

Earlier concepts of runoff during rainfall events are based on Hortonian flow where runoff is produced when the precipitation rate exceeds the infiltration rate of the soil (Horton 1933, 1945). This concept is commonly applied via the Soil Conservation Service Curve Number (SCS-CN) method where runoff is produced once effective precipitation exceeds initial abstraction and the amount of runoff produced is a function of a curve number that depends on plant cover and soil type (SCS-CN 1972). Since the early 1960's this concept has been challenged postulating that the majority of runoff is produced from a small percentage of the watershed that is saturated (Hewlett and Hibbert 1963). Dunne and Black (1970) found that runoff was produced from small, saturated areas next to streams and that the potential for runoff for any given location is correlated with its ability to become saturated. For any given storm event in a watershed, the majority of runoff is produced from a small percentage of saturated areas in the landscape. These areas are variable in size, increasing as surrounding areas become more saturated by precipitation or contributions from interflow (Bernier 1985). Steenhuis et al. (1995) demonstrated a methodology to incorporate VSA hydrology into hydrologic models using the SCS-CN method. This methodology has been successfully used in models discussed in the following sections.

VSA hydrology is especially important in humid, well-vegetated regions where infiltration rates generally exceed rainfall intensities. In upstate New York basins are characterized by highly conductive surface soils over shallow fragipans. The development of saturation-based runoff models is crucial for more effectively representing these areas.

VSA Hydrology in Hydrologic Models

Appling VSAs in hydrologic modeling not only improves hydrologic predictions but also improves predictions of pollutant loadings (O'Loughlin 1981) as saturated areas have been shown to be the largest contributing factor to pollution via dissolved solids (Walter et al. 2000, Gburek et al. 2002). The topographic index (1) is one method that is useful in describing where these saturated areas are more likely to occur (Beven and Kirkby 1979). It takes into account the unit length of the upland contributing area and slope to determine relative saturation of a point on the landscape and is defined by:

$$\lambda = \ln\left(\frac{a}{\tan\beta}\right) \qquad \textbf{(1)}$$

where a is the upslope contributing area per unit contour length and β is the local slope. Areas that are more likely to become saturated have a larger contributing area or a relatively smaller slope. Locations that are at the base of hillslopes and closer to streams are thus more saturated and likely to contribute to runoff than areas with less contributing area or smaller slope. TOPMODEL was the first model to be based on the topographic index and serves as a basis for other models that incorporate the index. The Soil and Water Assessment Tool (SWAT) and the Generalized Watershed Loading Function (GWLF) have both been successfully altered to integrate VSA hydrology in SWAT-VSA (Easton et al. 2009) and Variable Source Loading Function (VSLF) (Schneiderman et al. 2007).

Zollweg et al. (1996) conceptualized a distributed VSA based model through the Soil Moisture-based Runoff Model (SMoRMod) model. Its relatively simple structure and emphasis on important hydrologic characteristics in upstate New York categorize it as a favorable model for the region; however, it did not significantly improve stream flow predictions in comparison to other models. The Spatially Distributed Direct Runoff Model behaved similarly as it was used to route source areas to enhance predictions but it also did not significantly improve flow predictions (Buchanan et al. 2011).

SWAT-VSA and efficient distributed VSA models

The Soil and Water Assessment Tool (SWAT) is a semi-distributed, basin-scale hydrologic simulation model developed to help facilitate integrated water management (Arnold et al. 1998). It is supported by the EPA as a tool for total maximum daily load development and by other state agencies as a tool for guiding water resource related policy development and implementation. Although it was originally developed for application in the US, the expansion of its simulation capabilities has allowed it to become a globally used model. SWAT is a rather complex model that uses a large number of variables to parameterize the model. Easton et al. (2009) coerced a modified soils dataset into SWAT to reflect the topographic index in SWAT-VSA making the model able to implicitly route runoff from VSAs though built in routing procedures.

Thornthwaite and Mather (1955) developed a simple watershed model by keeping one average water balance for the root zone based on precipitation, estimated evapotranspiration and storage for the whole watershed. Successor watershed models based on this simple model divide the watershed up spatially and perform water balances for each area. Rain that falls in excess of field capacity (originally called "surplus water") either becomes runoff to a stream, or becomes recharge to an aquifer whose outflow may be modeled as a first-order reservoir. VSA watershed models developed by Collick et al. (2010) and Steenhuis et al. (2009) divided the watershed into high infiltration areas, low infiltration areas and saturated areas. Similar to the Thornthwaite Mather method, these models run one water balance for each of the three groups.

For the Steenhuis et al. model, excess rainfall from the infiltration and saturated areas becomes overland flow, and excess rainfall from the high infiltration area becomes recharge (to either a zero-order interflow reservoir or first-order groundwater base flow). The model uses a greatly reduced parameter set in comparison to SWAT as it takes in only 9 parameters per basin and simulates an unconfined aquifer for storage. In this parameter efficient model that is used here for comparison with SWAT, the user is able to adjust the available storage and fractional area covered by each grouping (saturated, degraded, and hillslope), and an additional three parameters for subsurface flow (duration of flow for the zero-order interflow group, the half-life of the first order interflow basin, and the maximum storage of the groundwater reservoir above which all remaining recharge becomes interflow).

Calibration of Hydrologic Models

There are two open source resources available to calibrate SWAT models: (1) auto-calibrations that are included with SWAT and (2) SWAT-Calibration and Uncertainty Programs (SWAT-CUP). Examples of procedures available included Parameter Solutions (ParaSol), Sequential Uncertainty Fitting (SUFI-2), and Sources of Uncertainty Global Assessment using Split-Samples (SUNGLASSES)(Abbaspour 2011). However, these procedures are not able to preserve representation of saturated areas during calibrations.

R is a statistical computing program (R Core Team 2012) that can be used as a calibration tool. Its high-level, interpreted scripting language provides flexibility in constraining parameters and selecting optimization criteria. Differential Evolution is a genetically based global optimization technique developed by Storn and Price (1997) that has been made available through R. It is most useful to solve systems of equations that are non-continuous and non-linear.

Study Areas

Black Creek and Little Tonawanda Creek are both located in Western New York State (Figure 1). The eastern watershed boundaries of Little Tonawanda adjoin the western watershed boundary of Black Creek although they are located in different basins. There is a large body of literature available for Black Creek because of water quality issues while very limited info is available for Little Tonawanda. Black Creek drains to the Genesee River and then flows north to Lake Ontario at Rochester. It is considered a major contributor to pollution in Lake Ontario and is in the process of TMDL development (NYS DEC 2003). Little Tonawanda Creek drains to Tonawanda Creek, meets with the Erie Canal and empties to the Niagara River at Tonawanda. The largest land use in Black Creek is agriculture followed by forest cover while Little Tonawanda is mostly forested (Table 1).

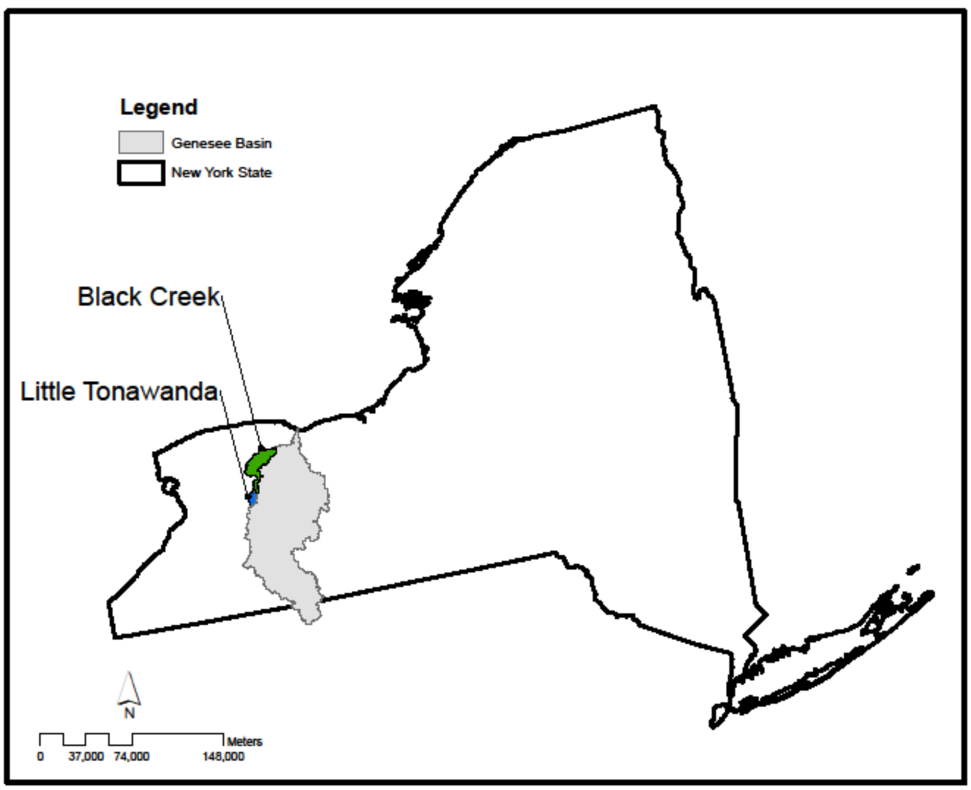


Figure 1. Location of study areas in relation to New York State

Table 1. Study area characteristics

Watershed	Watershed Area	Average Slope	Largest Land Use
Black Creek	34,626 ha	2.8%	Agriculture (46.62%)
Little Tonawanda	6,525 ha	10.1%	Forested (53.48%)

**Based on ArcGIS analysis of Land Cover Institute's National Land Cover Dataset 2006*

Little Tonawanda

Little Tonawanda Creek originates in Wyoming County, NY and is one of the headwaters of Tonawanda Creek. It lies in the Buffalo/Niagara Basin and covers an area of 6,525 ha. Average slope of the watershed is 10.1%. Flow direction is south to north passing through Linden and meeting up with Tonawanda Creek just south of Batavia. A major tributary to Little Tonawanda is Middlebury Brook. There are two swamps in the watershed: Bannan Swamp located at the most southerly extent of the watershed; and Webbers Swamp, which is 3 km north of Bannan Swamp (USGS-NHD, 2012). Stream flow observations are available from 1964 to 1992 at Linden (USGS-NWIS, 2012).

Black Creek

The Black Creek watershed covers 34,626 hectares across Genesee, Monroe, Orleans and Wyoming counties in Western New York (Autin et al 2003). It lies in the Lower Genesee River Basin adjoining the main stem just south of the Greater Rochester International Airport. Flow direction of the main stem is generally south to north, veering to the east midway through the watershed. The headwaters originate in the Genesee County Park that is mostly forested. Black Creek then flows south over the Onondaga Escarpment, through the Bergen-Byron Swamp and through the Churchville Reservoir. There are several tributaries to Black Creek including Spring Creek, Bigelow Creek, Robin's Book, North Branch Black Creek, Hotel Creek, and Mill Creek (Winslow 2012). Total relief of the watershed is about 214 meters from the headwaters to where it empties into the Genesee River leaving the region relatively flat with an approximate slope of 1%. There is a USGS stream gauging house that has been in use since October 1945 at Churchville located just downstream of the dam that forms the Churchville Reservoir (USGS-NWIS).

Climate

The study area is characterized as humid continental with winter lake effect snows from Lake Erie and Lake Ontario. Average annual air temperature in the region is 8.4 Celsius and average annual precipitation is 917 mm. Between 2.3 and 2.5 meters of snow fall on the area, annually. The climate stations used for this study were Batavia (GHCND: USC00300443) and Greater Rochester Airport (GHCND: USW00014768), which both have over 50 years of data through the present.

Land Uses

According the National Land Cover Dataset, 46.6% of the Black Creek watershed is used for agriculture (NLCD 2006), primarily dairy farms and vegetable crops. About 66.5% of the watershed is involved in Country Agricultural District Programs (Autin et al 2003). Of all the farms in the watershed, there are 11 dairy based farms with active confined animal feeding operations (CAFOs) in Black Creek (Winslow, 2012).

Other controlled sources of pollution in Black Creek include 31 State Pollutant Discharge Elimination System (SPDES) permitted facilities along with 25 areas classified as mines, quarries or disturbed areas (Autin et al. 2003). There are four wastewater treatment outfalls in Black Creek and one that is no longer in function at Churchville (Winslow 2012) (Figure 2). Byron has three outfall locations in North, South and Central Byron. The fourth WWTP is located in Bergen (EPA). While these pollutant sources do not significantly affect streamflow hydrology, they are important to the context of TMDL assessment.

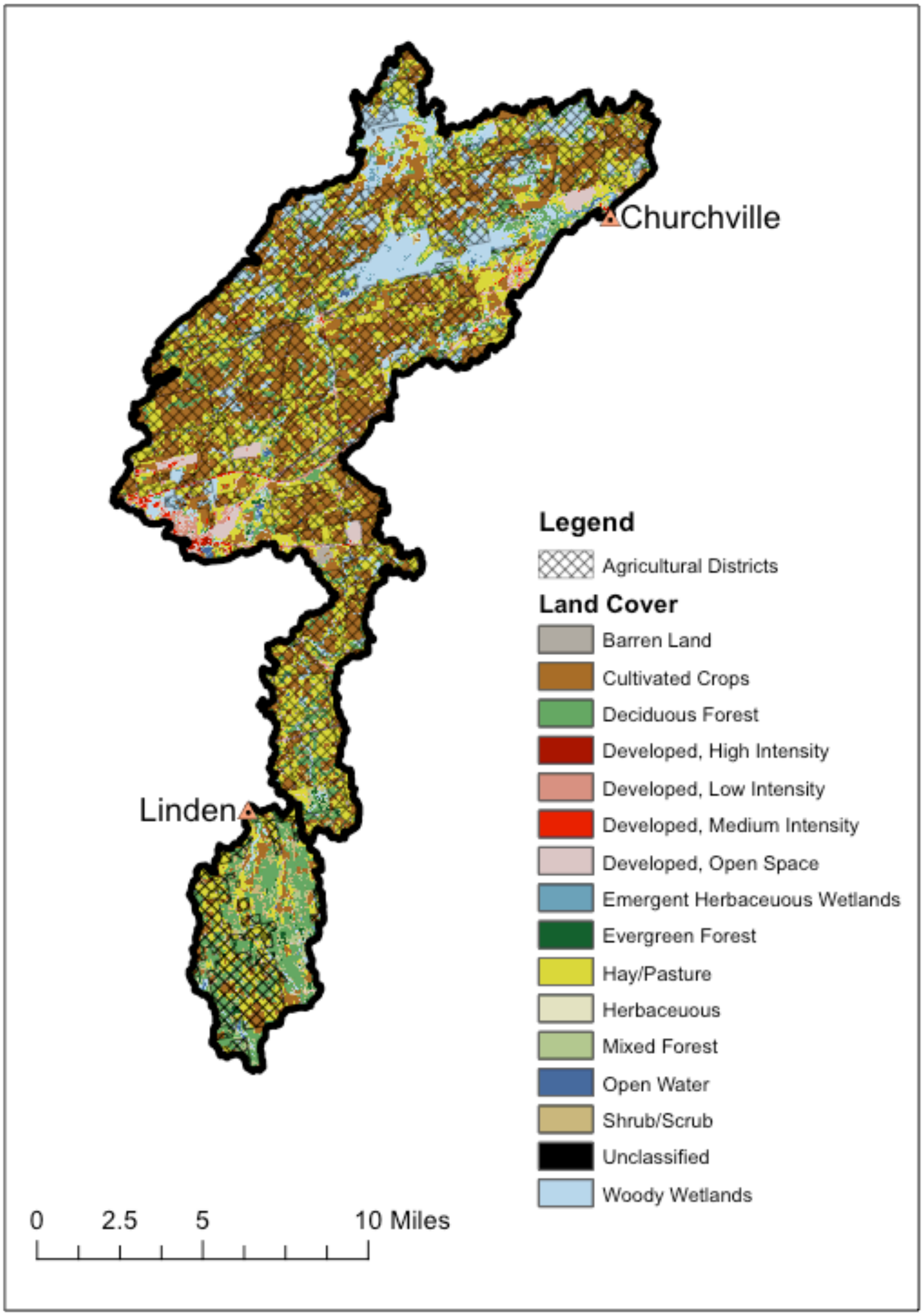


Figure 2. Agricultural districts and land use in Black and Little Tonawanda Creek. Stream gages at Linden and Churchville also shown.

Geological Features

The central section of the watershed includes the Niagara Escarpment (King and Beikman 1974) and is underlain with limestone and dolostone (Autin et al. 2003); areas north and south of the carbonate rock of the Niagara Escarpment is mostly shale except for more dolostone at the northern extremity. Rock layers can be found in Figure 3. Running through the central portion of the Black Creek watershed is the Onondaga Formation, which is known to be a conduit for rapid groundwater transport (Richards et al. 2010) and pollutants in the area (Fronk 1994). Fronk (1994) traced TCE spills traveling east through the Onondaga. Some studies of the Onondaga have observed large water table fluctuations (Staubitz and Miller 1987, Kappel and Miller 1996, Dunn 1992). One study just north of the region reported regional ground water tables above the surface (Yager et al 2007). Richards et al. (2010) noted that the soils in the study area are thin and that sink hole and bedrock fractures store groundwater.

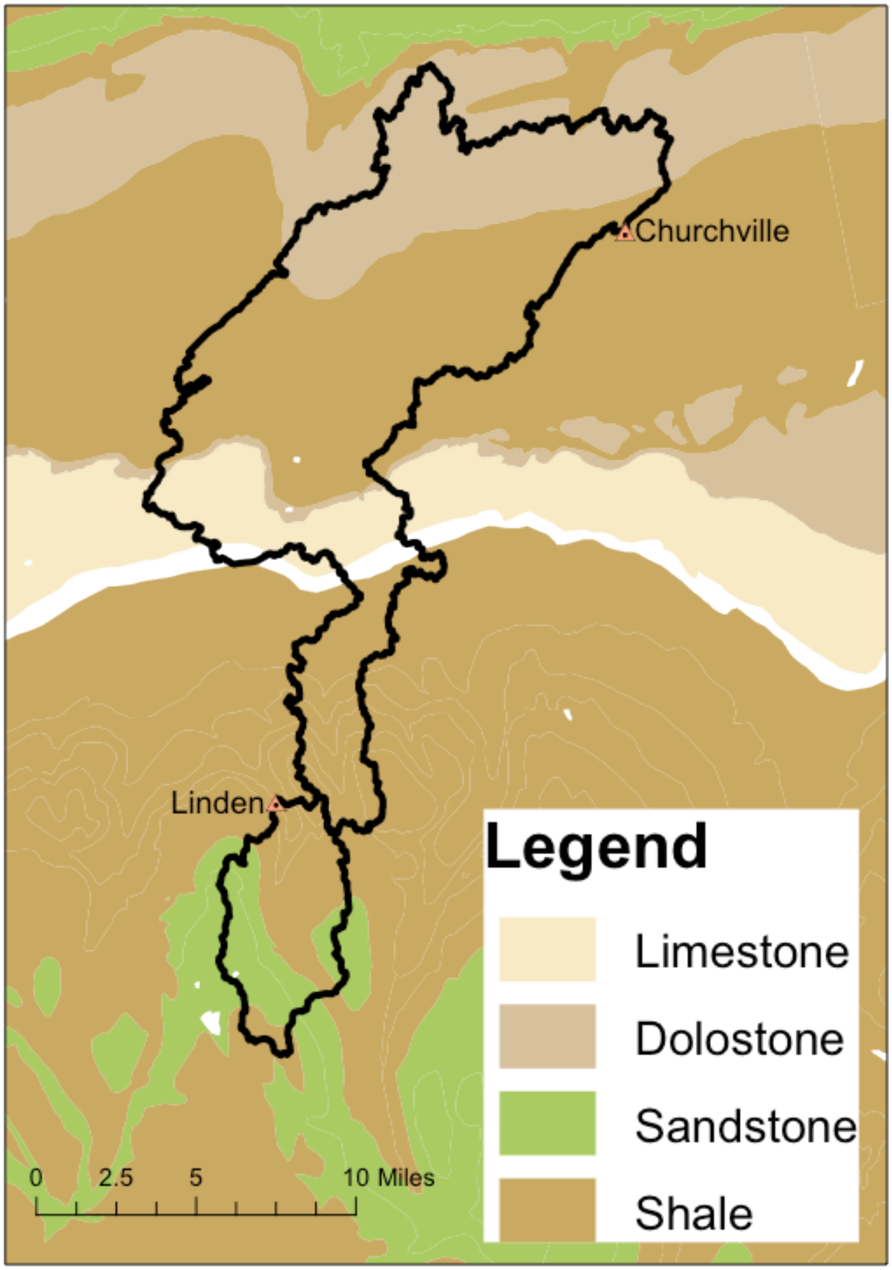


Figure 3. Underlying composition of study area.

The Bergen-Byron Swamp is located on Black Creek in Genesee County within the municipalities of Byron and Bergen. The largest wetland in the watershed, it covers about 800 hectares (Hall 2005). Water entering via interflow to the swamp has been observed to be calcareous and deposit marl picked up from the dolomite to the north and limestone from the south (Seischab 1984, Futyma and Miller 2001).

Soils

The basin's soils are underlain with limestone, dolostone, sandstone and shale bedrock. The limestone and dolostone are associated with calcareous soils with high lime content. Areas north of the Onondaga generally have deeper soils while other southerly regions have shallower soils. Organic matter content is higher within and surrounding the swamp (Autin et al. 2003). The State Soil Geographic (STATSGO) Database maps indicate that soils in the study area are likely to produce moderate runoff. For purposes of equations described later, soils that are more likely to produce runoff are classified as D while soils that are less likely to produce runoff are classified A. In Table 2 below, the majority of soils in Black Creek (57.5%) are listed as hydrologic soil group B. Little Tonawanda's soils are fall mainly into group C (76.3%) (NRCS 2012).

Table 2. State Soil Geographic Hydrologic Soil Groups (% of basin area)

Hydrologic Soil Groups	A	B	C	D
Black Creek	4.9	57.5	33.4	4.3
Little Tonawanda	0	22.2	76.3	1.4

Water Body Impairment

Many sections of Black Creek are listed on the NYS 303(d) list as impaired. Sources of impairment in the upper regions include agricultural land use, confined animal feeding operations (CAFOs) and the South Byron WWTP. These sources have been found to contribute harmful quantities of phosphorus contributing to aquatic life impairment in both the upper and lower section of the watershed. The middle reaches also receive pollution from industrial and municipal sources as well as septic systems, urban runoff and deicing storage, among others (GFLRPC 2006). However, in the middle reaches, algal growth is the prominent impairment. They are class C waters whose best usage is fishing. They were placed on the list in 2004 (NYS 2012 Draft 303(d) list). There are no known water body impairments in Little Tonawanda Creek.

Stream flow Data

Stream flow data is available at two locations for the study area, one on each creek. One stream gage station is located on Black Creek located in Churchville, NY (04231000) and is maintained by Monroe County Environmental Health, National Weather Service, U.S. Army Corp of Engineers in Buffalo, and the U.S. Geological Survey. Drainage area above the station, located downstream of Bergen-Byron Swamp, just after the Churchville Reservoir, is 346 km^2. Average daily gage height and stream flow is available from October 1945 to the present (USGS). The gage at Little Tonawanda is no longer operational but has data available for the time period in this study. Measurements were recorded at Linden, NY (04216500) from August 1912 to September 1992. Drainage area of the watershed is 57 km^2 (USGS).

Methods and Materials

Precipitation Alterations

One precipitation data set was used for each of the two watersheds: Batavia for Little Tonawanda and Rochester International Airport for Black Creek. For each precipitation dataset, three alternative data sets were derived to determine the effect on model output. Data from Batavia were offset backwards by one day so that 24-hour, morning-reported precipitation figures were more consistent with midnight-to-midnight reported daily averaged stream flow. The Rochester Airport station reports precipitation in sync with stream flow. Each set was modified to account for measurement uncertainty as suggested by Larson and Peck (1974). Internal snowmelt functions used by the SWAT model were disabled and daily snowmelt was calculated externally according to the process-based model by Walter et al. (2005). This model uses an energy balance of the snow pack to determine how much snow is remaining as snow and how much is melting. The main equation used is:

$$\lambda \Delta SWE = +L_a - L_t + H + E + G + P - SWE(C\Delta T_s) \qquad (2)$$

where λ is the latent heat of fusion, ΔSWE is the change in snowpack water equivalent, S is the net incident solar radiation, L_a is the atmospheric long wave radiation, L_t is the terrestrial long wave radiation, H is the sensible heat exchange, E is the energy flux associated with latent heats of vaporization and condensation at the surface and G is ground heat conduction to the bottom of snowpack, P is the heat added by rainfall and SWE($C\Delta T_s$) is the change of snowpack heat storage). This change allowed both SWAT and PED model types to use the same snowmelt functions and to utilize a process based snowmelt model that has shown to be more effective at predicting snowmelt (Zhang et al. 2008). The following is a list with description of precipitation datasets used for the models:

Calibration was performed for 1979 to 1984 and validation for 1985 and 1986. Since rainfall is reported for a different 24-hour period than the daily averaged flow, the rainfall day was moved up one day in the cases when the peak runoff was one day after the rainfall day,

1. **Snowmelt**. Raw precipitation data was processed through the snowmelt model. Some small changes were made to adjust for the fact that the precipitation includes part of the previous day. In 10 cases total (for calibration and validation time periods), precipitation was moved to a day later.
2. **Increased Snowmelt**. Snowmelt events in dataset (1) were multiplied by a factor of 2 for Little Tonawanda and 1.2 for Black Creek so that the average observed and predicted flow were approximately equal (within 10%).

3. **Snowmelt+adjusted.** Less than 2% of all days from (2) were changed to achieve better alignment of precipitation and flow.

The validation years were simulated with the following

1. Snowmelt. Same scenario as (1) for calibration.
2. Increased snowmelt. This set was developed by multiplying all snowmelt events with a factor of 2 for Little Tonawanda Creek so that the average observed and predicted flow were approximately equal (within 10%). Representation of Black was not improved by increasing snowmelt events so this dataset was not used for Black Creek.
3. Snowmelt+adjusted. Same as (3) for calibration.

Parameter Efficient Distributed (PED) Model

The Parameter Efficient Distributed (PED) model was developed to better predict discharge and sediment loss in Ethiopian basins. The model divides a watershed into saturated areas and hillslopes. Hillslopes are then further divided into high infiltration areas and low infiltration areas (also referred to as degraded). Saturated areas are valley-like regions that become saturated more easily contribute most to runoff while high infilration areas allow percolation routing flow to the subsurface. Low infiltration areas store some water before contributing to subsurface flow but can also contribute to runoff once saturation is reached.

The following description is from Tesemma et at. 2010 and Steenhuis et al. 2009. A Thornthwaite-Mather water balance (1955) is kept for each of the 3 areas (1) saturated, (2) high infiltration hillslopes, and (3) low infiltration hillslopes as:

$$S_s(t) = S_s(t - \Delta t) + \left[P - E_a - R - P_{erc}\right]\Delta t \qquad (2)$$

P precipitation (LT^{-1})
E_a actual evapotranspiration (LT^{-1})

$S_s(t)$ water storage in soil profile at time t at some distance L above the restrictive layer
$S_s(t-\Delta t)$ water storage at previous time step at L above restrictive layer
R saturation excess runoff (LT^{-1})
P_{erc} percolation to the subsoil (LT^{-1})
Δt time step (T)

Actual evaporation when precipitation, P, is below potential evaporation, E_P, for the time step is described by

$$E_a = E_p \left[\frac{S_r(t)}{S_{r\max}} \right] \tag{3}$$

$S_r(t)$ soil moisture at time *t* for root zone
$S_{r\,max}$ field capacity moisture content for the permeable hillside and saturated moisture content for runoff areas

Soil moisture is then computed according to Steenhuis et al. 2009 where is it described in exponential form based on the previous time step's soil moisture:

$$S_r(t) = S_r(t-\Delta t) \exp\left[\frac{(P-E_p)\Delta t}{S_{r\max}} \right] \quad \text{when } P<E_P \tag{4}$$

High infiltration areas can route excess water (P_{erc}) to interflow (Q_{if}) or baseflow (Q_{bf}) where it can be added to the reservoirs for each area (S_{if} for interflow and S_{bf} for baseflow). Storage below the maximum allowed storage and outflow from the baseflow reservoir is described by

$$S_{bf}(t) = S_{bf}(t-\Delta t) + [P_{erc} - Q_{bf}(t-\Delta t)]\Delta t \tag{5}$$

$$Q_{bf}(t) = \frac{S_{bf}(t)\big[1-\exp[-\alpha\Delta t]\big]}{\Delta t} \tag{6}$$

α reservoir coefficient (T^{-1})

Above the maximum storage, baseflow storage from the previous time step becomes the maximum in equation (6). Once the baseflow reservoir is full, interflow begins and is described by

$$Q_{if}(t) = \sum_{\tau=1}^{\tau \le \tau^*} 2P_{erc}^*(t-\tau)\left[\frac{1}{\tau^*} - \frac{\tau}{\tau^{*2}}\right], \tau \le \tau^* \qquad (7)$$

τ^* duration of time after precipitation that interflow stops

$Q_{if}(t)$ interflow at time step t

P^*_{erc} (t-τ) effective percolation on day (t-τ)

See Steenhuis et al. (2009) for more detail.

Soil and Water Assessment Tool

USDA's Soil and Water Assessment Tool (SWAT) is a semi-distributed, hydrologic non-point source model developed to simulate basins whose main land use is agriculture (Arnold et al. 1998). SWAT initially breaks a basin into subbasins that serve to spatially distribute the model. Areas that respond similarly in the watershed, termed hydrologic response units (HRUs) are defined by the coincidence of land use, soil type and slope. The response of each HRU group is lumped and routed to a defined stream network within each subbasin and then routed for the entire basin. Climate data can also be a forcing variable for the model but a weather generator is available that uses historical weather data for predictions. The model can be run on daily, monthly or yearly time scales and simulates interflow, plant uptake, and erosion, as well as many other hydrologic processes.

SWAT Inputs and Alterations

For model initialization, which includes basin delineation and HRU definition, we chose ArcSWAT Beta 3 release (for use with SWAT 2009) and ESRI's ArcMap10. The digital elevation model (DEM) for basin delineation was obtained from the U.S Geological Survey's 2009 National Elevation Dataset (NED) via Seamless Data Server for the study regions at a resolution of 1/3 arc-second (10 m in this study area). The 2006 National Land Cover Dataset was used as the land use input to the model with 30 meter cell size. A methodology for incorporating variable source areas (VSAs) into SWAT (SWAT-VSA) begins with a topographic index (TI) map that when quantized into ten classes provides polygons that serve in place of USDA STATSGO or SSURGO soil polygons normally used in ArcSWAT (see Easton et al. 2009). SWAT and SWAT-VSA use identical executable files but differ in how the soils information is incorporated. Each TI class polygon is defined with soil parameters such as available water capacity and hydraulic conductivity. These can come from SSURGO or STATSGO polygon overlays on the TI class polygons. For this study, the Harmonized World Soil Database (FAO 2012) was used with a resolution of 5 arc seconds (FAO) for soil parameters. HRUs were defined by thresholds of 15/1/50 (land use/soil/slope) where a land use, soil class or slope class must be greater than the threshold value in order be considered in the HRU delineation. Daily minimum and maximum temperature and precipitation was retrieved from the National Climatic Data Center (NOAA-NWS 2011).

Defining Variable Source Area Hydrology Theory with the Curve Number

The curve number was originally developed by the Soil Conservation Service to predict runoff in ungauged watersheds. It was designed to account for many different land uses, soil types and general variability by assigning a number that roughly corresponds to the likelihood of an area to produce runoff (Rallison and Miller, 1981). Predicting surface runoff is done using the following equation:

$$Q = \frac{(P - 0.2S)^2}{(P - 0.2S + S)} \qquad (8)$$

Where

Q = surface runoff (mm)

P = effective precipitation (mm)

I_a = initial abstraction (mm)

S = effective storage (mm)

Runoff is produced when the effective precipitation after initial abstraction exceeds the effect storage of the watershed. Storage capacity of the watershed (S) in mm can be estimated in standard SWAT

$$S = 25.4\left(\frac{1000}{CN} - 10\right) \qquad (9)$$

CN is the curve number that determines the amount of storage produced by soil, land use type, slope and antecedent moisture conditions. These values are tabulated from previous research and observations.

Steenhuis et al (1995) reconceptualized the curve number to reflect variable source area hydrology theory by defining the fractional area of the watershed contributing to runoff as the depth of excess precipitation between runoff occurrence and saturation divided by the effective precipitation at the same time step described by:

$$A_f = \frac{\Delta Q}{\Delta P_e} \qquad (10)$$

Where

ΔQ = excess runoff generated during a storm

ΔP_e = precipitation after runoff is generated or $P_e = P - I_a$

After differentiating Q in Eq. 3 with respect to P_e, the fractional saturated area can be derived as a function of cumulative effective precipitation and a water storage coefficient S_e:

$$A_f = 1 - \frac{S_e^2}{(P_e - S_e)^2} \qquad (11)$$

There are two aspects of SWAT input data preparation that were redefined to create SWAT-VSA. First, the varying contributing areas were changed so they are based on relative local saturation likelihoods in the watershed. The second is in how the HRU's are defined. In conventional SWAT initializations, HRUs are defined by grouping similar areas in terms of land use, soil and slope. After determining the spatial distribution of expected saturation and runoff using TI classes, a replacement spatial soils database was created defined in terms of TI class. The layer is loaded in as soils information and ArcSWAT uses the new data to define HRUs. For application to SWAT-VSA, values of the topographic index were equally divided into 10 groups where the value of 1 corresponds to areas that are less saturated and a value of 10 corresponds to areas that have a greater potential to be saturated. Modelers can choose the number of TI classes that a given watershed should be divided into depending on the heterogeneity of the watershed.

Governing Routing Equations in SWAT

The following is a summary of the equations used in SWAT to simulate runoff, groundwater and interflows. When precipitation falls on a given area, the water will either leave immediately as surface runoff or infiltrate into the soil where it enters into soil storage. It may evaporate from storage if in the shallow soil layers, percolate to groundwater or move horizontally via interflow. A portion of the infiltrating water will enter into either the shallow aquifer (where flow leaving is considered groundwater flow) or the deep aquifer, which is assumed to drain outside of the basin. During dryer soil conditions, water can move upward from the shallow aquifer to the overlying soil layer in a process SWAT calls revap. The user sets a threshold value for this to occur. Runoff is described with the SCS-CN equation discussed previously.

Groundwater

Once water in the shallow aquifer exceeds a threshold set by the user, the following governs:

Steady-State response of groundwater flow.

$$Q_{gw} = \frac{8000 * K_{sat}}{L^2_{gw}} h_{wtbl} \qquad (12)$$

Q_{gw}=groundwater flow (mm H_2O)
K_{sat}=hydraulic conductivity (mm/day)
L_{gw}=distance from the ridge or subbasin divide for groundwater system (m)
h_{wtbl}=water table height (m)

Unsteady state groundwater flow

$$Q_{gw,i} = Q_{gw,i-1} \exp[-\alpha_{gw} \Delta t] + w_{rchrg,sh} (1 - \exp[-\alpha_{gw} \Delta t]) \quad \text{if } aq_{sh} > aq_{shthr,q} \qquad (13)$$

$$Q_{gw,i} = 0 \quad \text{if } aq_{sh} \le aq_{shthr,q} \qquad (14)$$

$Q_{gw,i-1}$=groundwater flow on day i-1 (mm H_2O)
α_{gw}=baseflow recession constant
Δt=time step (day)
$w_{rchrg,sh}$=amount of recharge entering shallow aquifer on day I (mm H_2O)
aq_{sh}= amount of water stored in shallow aquifer at beginning of I (mm H_2O)
$aq_{sh,thr,q}$= amount of water stored in shallow aquifer at beginning of I (mm H_2O)

Revap

Water can also move upward through the soil profile by a mechanism that SWAT calls "revap." This process takes place when the overlying soil layer is dryer and draws water from the shallow aquifer. Maximum revaporation is determined by:

$$w_{revap,mx} = \beta_{rev} E_o \qquad (15)$$

$w_{revap,mx}$=maximum amount of water moving into the soil zone in response to water deficiencies (mm H_2O).
β_{rev}=revap coefficient
E_o=potential evaporation for the day (mm H_2O)

Actual water that will be lost to revaporation is decribed by the following algorithm:

$w_{revap}=0$ if $aq_{sh} \le aq_{shthr,rvp}$ (16)

$w_{revap}=w_{revap,mx}-aq_{shthr,rvp}$ if $aq_{shthr,rvp} < aq_{sh} < (aq_{shthr,rvp} + w_{revap,mx})$ (17)

$w_{revap}=w_{revap,mx}$ if $aq_{sh} \ge (aq_{shthr,rvp} + w_{revap,mx})$ (18)

Interflow

Interflow in the soil profile occurs when soil available water is at field capacity.

$$Q_{lat} = 0.024\left(\frac{2SW_{ly,excess}K_{sat}slp}{\phi_d L_{hill}}\right) \qquad (19)$$

where

$SW_{ly,excess}$=water content of soil layer on day (mm H_2O)
K_{sat}=saturated hydraulic conductivity of soil (mm/day)
slp= slope (m/m)
ϕ_d= drainable porosity of the soil layer (mm/mm)
L_{hill}= hillslope length (m)

Calibration and Validation of SWAT

Models were assessed using Nash Sutcliffe Efficiency (NSE) (Nash and Sutcliffe 1970), percent bias (Yopa et al. 1996) and the coefficient of determination r^2. The NSE is a measure of how closely simulated values agree with observed values and is defined by:

$$NSE = 1 - \frac{\sum (Q_{sim,i} - Q_{obs,i})^2}{\sum (Q_{obs,i} - \overline{Q}_{obs})^2} \qquad (20)$$

where $Q_{sim,I}$ is the simulated flow value, $Q_{obs,I}$ is the observed value at the same time step and $\overline{Q}_{obs}$ is the mean value of observed flow values over the entire calibration or validation time period. Percent bias is a measure of whether simulated flow tends to over or underestimate observed data and is defined as:

$$PBIAS = 100\left[\frac{\sum \left(Q_{sim,i} - Q_{obs,i}\right)}{\sum Q_{obs,i}}\right] \qquad (21)$$

r^2 is a measure of the proportion of variance in observed flows explained by the model.

$$r^2 = \left(\frac{\sum_{i=1}^{n} (Q_{sim,i} - \overline{Q}_{sim})(Q_{obs,i} - \overline{Q}_{obs})}{\sqrt{\sum_{i=1}^{n} (Q_{sim,i} - \overline{Q}_{sim})} * \sqrt{\sum_{i=1}^{n} (Q_{obs,i} - \overline{Q}_{obs})}} \right)^2 \qquad (22)$$

Sensitivity analysis was performed using the package included with ArcSWAT that varies one parameter at a time using the Latin Hypercube Sampling procedure. Analysis was performed on all flow parameters prior to calibrations; the ten most sensitive parameters for Little Tonawanda and Black Creek can be found in Table 3 and Table 4, respectively. Ten hypercube intervals were used with a 5% parameter change for each sample population.

Table 3. Sensitivity analysis results for Little Tonawanda Creek

Parameter	Ranking	Description
SURLAG	1	Surface Runoff Lag Factor
CN2	2	Curve Number-Antecedent Moisture Condition 2
CANMX	3	Maximum Canopy Coverage
ESCO	4	Evaporative Soil Compensation Factor
SOL_Z	5	Soil Depth
BLAI	6	Maximum Potential Leaf Area Index
Slope	7	Slope
SOL_K	8	Soil Hydraulic Conductivity
SOL_AWC	9	Soil Available Water Capacity
CH_K2	10	Hydraulic Conductivity of Channel

Table 4. Sensitivity analysis results for Black Creek

Parameter	Ranking	Description
CN2	1	Curve Number-Antecedent Moisture Condition 2
ESCO	2	Evaporative Soil Compensation Factor
SOL_AWC	3	Soil Available Water Capacity
BLAI	4	Maximum Potential Leaf Area Index
CANMX	5	Maximum Canopy Coverage
SOL_Z	6	Soil Depth
Slope	7	Slope of soil fragipan
SOL_K	8	Soil Hydraulic Conductivity
ALPHA_BF	9	Baseflow Alpha Factor
SURLAG	10	Surface Runoff Lag Factor

The models for Black and Little Tonawanda Creeks were calibrated using R (R Development Core Team, 2012) with various published Comprehensive R Archive Network packages including EcoHydRology, SWATmodel, DEoptim, and topmodel. Differential Evolution (Storn and Price, 1997) was used to calibrate using an objective function defined using the Nash Sutcliffe Efficiency (Nash and Sutcliffe 1970) where the function to be reduced was

$$ObjectiveFunction = \left| \frac{\sum (Q_{sim,i} - Q_{obs,i})^2}{\sum (Q_{obs,i} - \overline{Q}_{obs})^2} - 1 \right| \qquad (23)$$

where $Q_{sim,I}$ is the simulated flow value, $Q_{obs,I}$ is the observed value at the same time step and $\overline{Q}_{obs}$ is the mean value of observed flow values over the calibration time period. This function can be applied for a variety of time steps including daily, monthly, seasonally or yearly evaluations. Calibrations started with curve number assigned to the corresponding TI classes (Table 5). They were halted once the objective function was no longer changing.

Table 5. Calculated curve number for each TI class

Curve Number	TI Class
99	10
97	9
94	8
91	7
88	6
83	5
78	4
71	3
61	2
41	1

The parameter efficient model was calibrated by varying the parameter values by hand. Partial areas were estimated first by closing the water balance, then interflow and baseflow parameters were estimated followed by the maximum storages in the root zone. These steps were repeated several times.

Both watershed models were simulated from January 1, 1979 to December 31, 1986 including a two-year warm-up period. Calibrations were completed using 1/1/1979 to 12/31/1984 data and validation using 1/1/1985 to 12/31/1986 data. This time period was chosen as it was the longest running time period with precipitation data closest to available sediment observations available that are significant to TMDL implementation. Water balances for the watershed were calculated on monthly, seasonal and yearly time steps for runoff, groundwater, and interflows. They were also computed for each TI class.

Results

Precipitation Comparison

Overall, the monthly differences between results using the three precipitation datasets are fairly minimal (Figure 4). No adjustments were made during the summer months. Much of the increase in snowmelt was seen in March when melting events occurred. The addition is accounted for in lower precipitation in January when snow is accumulating and in the misrepresentation of snowfall by precipitation gages. Overall, dataset (3) for Little Tonawanda saw the greatest snowmelt water increase at 36% above observed. The lowest was from (1) Little Tonawanda and (3) Black Creek at a 5.9% increase.

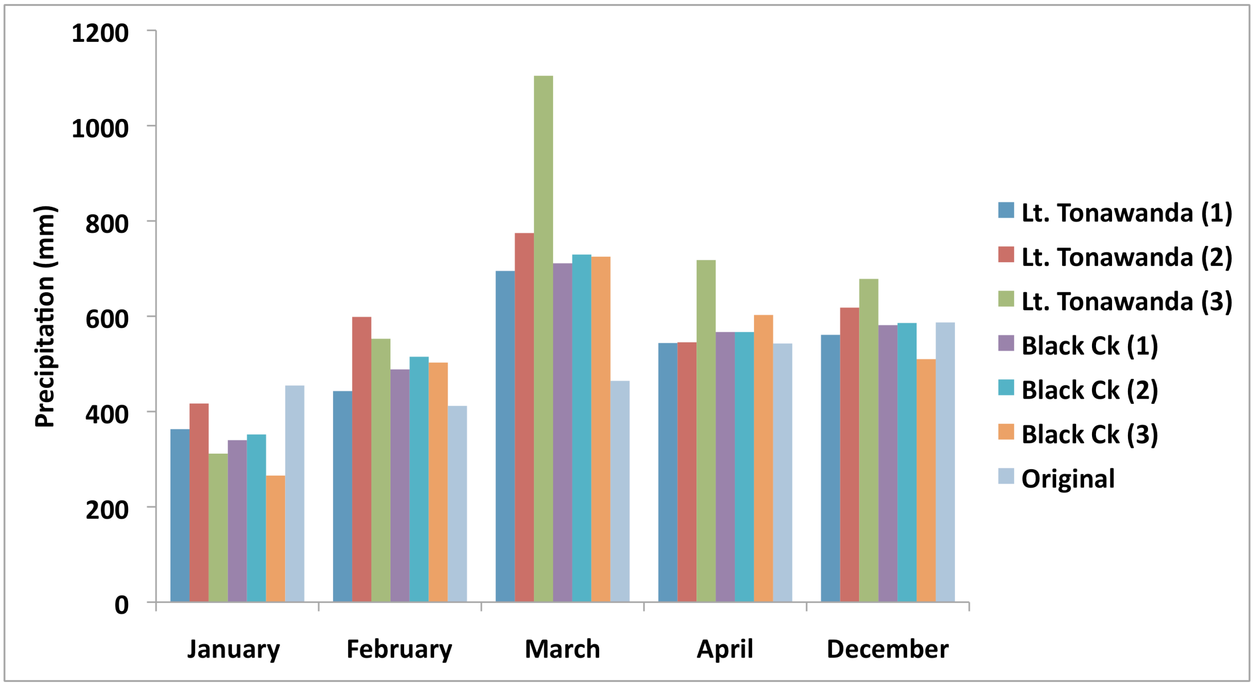


Figure 4. Sum of monthly precipitation data from 1979-1984 for each dataset . 1, 2, and 3 refer to the precipitation datasets previously described (1) snowmelt, (2) increased snowmelt, and (3) snowmelt+adjusted

SWAT Parameters

Using the TopoSWAT tool (an ArcToolbox script) that creates topographic index classes based on soil and slope inputs, the map in Figure 5 was produced. Areas that have a lower TI class are less saturated and thus less likely to produce runoff. Areas that are classified in a higher TI class are more often saturated and are more likely to produce runoff. The location of Little Tonawanda creek can be clearly seen in Figure 5 from the collection of higher TI classes in the central portion of the watershed.

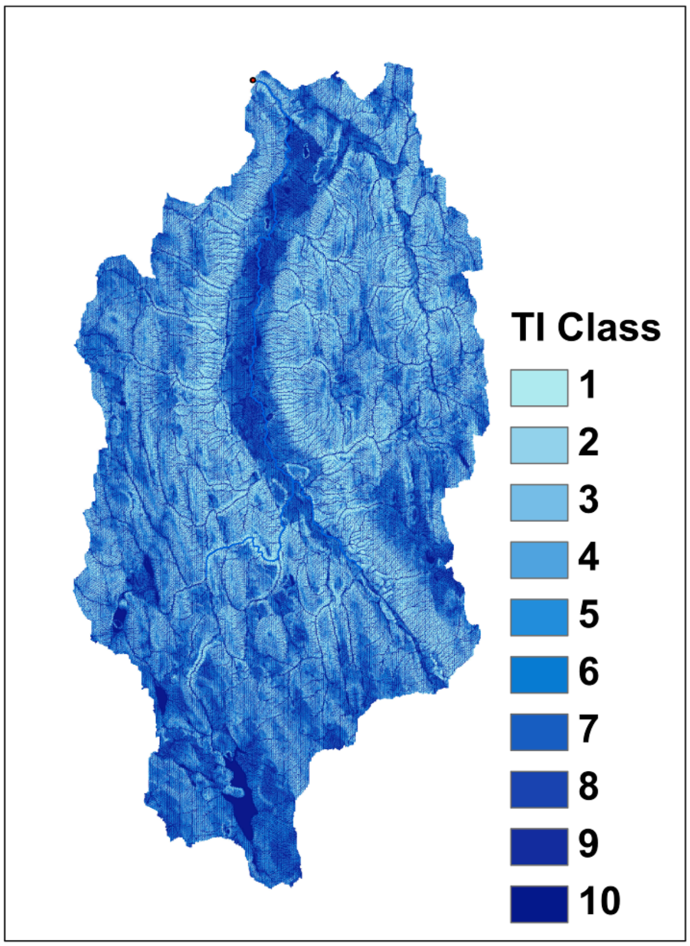


Figure 5. Map of Little Tonawanda Creek TI Classes. 1=least saturated, 10=most saturated

Initial curve numbers were assigned to TI classes based on the TI index where the highest, most saturated TI classes have a high curve number and lower, least saturated areas have lower curve numbers. During calibration, parameter constraints were bounded to preserve the curve numbers assigned to each TI class. For example, curve numbers for lower TI classes were bounded from 50-60 if the initial curve number was 55. This maintains the expected relative curve number values of TI classes. Curve number values for Little Tonawanda maintained an even distribution through calibration and did not change significantly from initial assignments (Table 6).

Table 6. Little Tonawanda TI Class Areas with Initial and Calibrated Curve Numbers

TI Class	Area (ha)	Fraction of Total Area	Initial Curve Number	Post Calibration Curve Number
1	664	0.12	41	40
2	583	0.10	61	57
3	554	0.10	71	66
4	555	0.10	78	72
5	585	0.10	83	76
6	565	0.10	88	78
7	568	0.10	91	80
8	539	0.09	94	82
9	561	0.10	97	84
10	531	0.09	99	86

A map of Black Creek by TI class can be found in Figure 6. Location of the stream is not as obvious as with Little Tonawanda Creek. This could be due to the lower average slope of the watershed not clearly delineating the stream network and the larger relative size of the watersheds with the same TI class distribution. The Bergen-Byron Swamp, located in the upper, central portion of the watershed approximately 8 km from the USGS station at Churchville, can be distinguished somewhat by the collection of higher TI classes but is not easily identifiable from the TI class map.

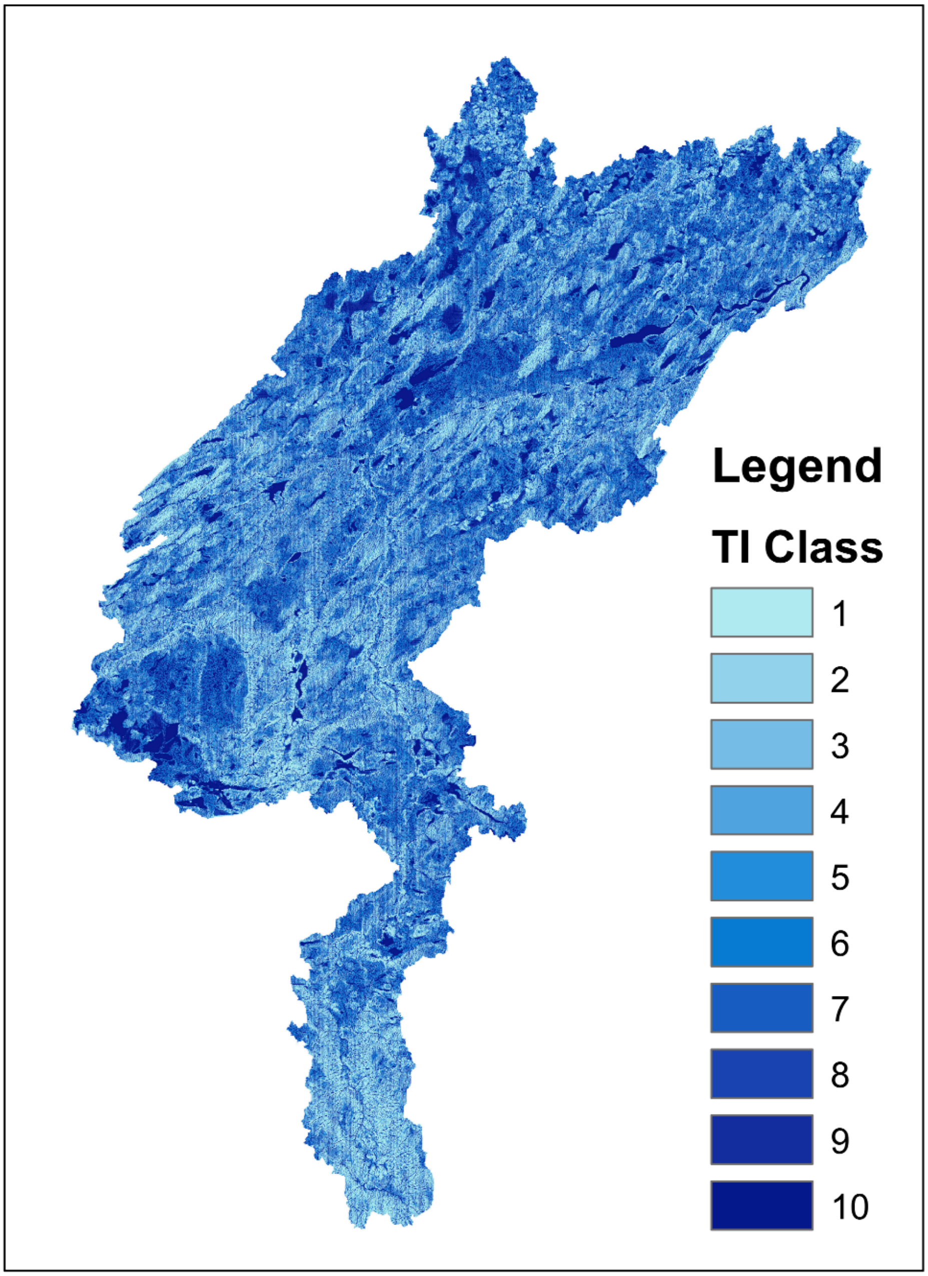


Figure 6. Black Creek TI Class Distribution, 1=least saturated, 10= most saturated

Final curve number values for Black Creek can be found in Table 7 along with the areas for each. Similar to Black Creek, areas were fairly evenly distributed across the watershed. Curve number values for the lower 5 TI classes tended to drift toward lower curve numbers during calibration while the upper 5 tended to drift toward higher curve numbers.

Table 7. Black Creek TI Class Areas with Initial and Calibrated Curve Numbers

TI Class	Area (ha)	Percent of Total Area	Initial Curve Number	Post Calibration Curve Number
1	3988	0.12	41	31
2	4004	0.12	61	35
3	3689	0.11	71	37
4	3832	0.11	78	39
5	3372	0.10	83	64
6	3206	0.09	88	76
7	3387	0.10	91	79
8	3379	0.10	94	81
9	3200	0.09	97	93
10	2569	0.07	99	95

PED Parameters

The calibration years for the PED model were simulated with the same set of parameter values for each precipitation series. The parameters used for both watersheds are listed in Table 8 (Little Tonawanda) and Table 9. (Black Creek). The PED model was first calibrated by adjusting the area fractions to obtain a reasonable distribution of direct runoff and interflow. Next the interflow parameters are adjusted and finally the maximum storages. This process is repeated until the best Nash Sutcliffe coefficient is obtained (Tesemma et al. 2010).

Table 8. Calibrated parameters used in the PED model for Little Tonawanda Creek

	Area (fraction of watershed)	Maximum Storage (mm)
Saturated Area	0.1	150
Low infiltration Area	0.1	5
High Infiltration Area	0.8	130
Half-life of aquifer	14	days
Maximum Storage	40	mm
t*	4	days

Table 9. Calibrated parameters used in the PED model for Black Creek

	Area (fraction of watershed)	Maximum Storage (mm)
Saturated Area	0.07	150
Low Infiltration Area	0	5
High Infiltration Area	0.93	400
Half-life of aquifer	14	days
Maximum Storage	40	mm
Initial Storage	40	mm
t*	6	days

Results

SWAT and Parameter Efficient Distributed (PED) Model

Little Tonawanda

Final model calibration for the snowmelt+adjusted dataset yielded a daily Nash Sutcliffe Efficiency (NSE) of 0.55 for SWAT and 0.62 for PED for Little Tonawanda Creek. For both models, the snowmelt+adjusted dataset had the best metrics while the snowmelt dataset was least. All metrics for both models can be found in Table 10.

Table 10. Little Tonawanda metrics for both SWAT and PED models

	SWAT	PED
Nash Sutcliffe Efficiency		
Snowmelt	0.36	0.35
Increased Snowmelt	0.4	0.33
Snowmelt+adjusted	0.55	0.62
Percent Bias		
Snowmelt	-29.4	-25.4
Increased Snowmelt	-26.7	-21.3
Snowmelt+adjusted	-17.4	-10.3
R^2		
Snowmelt	0.45	0.37
Increased Snowmelt	0.46	0.38
Snowmelt+adjusted	0.57	0.38

The greatest percent bias was -29.4% for the snowmelt dataset while the smallest was reported for the snowmelt+adjusted series (-17.4%). This indicates that SWAT under predicted flows from the watershed, which could be due to overestimation of evapotranspiration by the model, under estimated precipitation, or overestimated deep recharge. R-squared for simulated versus observed values was 0.57 for the best simulation (snowmelt-adjusted) and 0.45 for the worst (snowmelt). These metrics suggest that the model tended to predict lower flow values than observed data. Hydrographs for calibration years 1981-1984 were difficult to read with multiple plot lines so a representative period was chosen for analysis. This period was the winter of 1984 to illustrate the effect of the different precipitation adjustments. Hydrographs for all four calibration years as well as the year 1981 can be found in the Appendix (A. 1 and A. 2 for SWAT and A.3 and A. 4 for PED). Figure 8 and Figure 10 show the PED and SWAT, respectively, hydrographs for winter 1984.

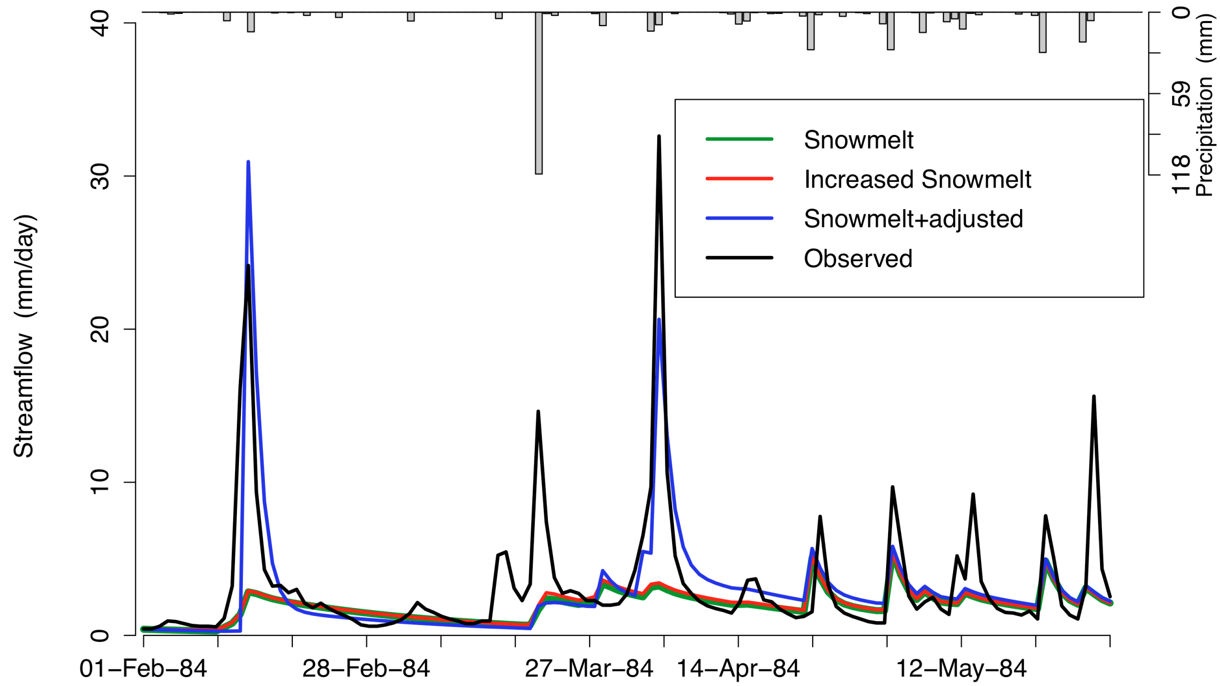


Figure 7. SWAT Little Tonawanda winter 1984

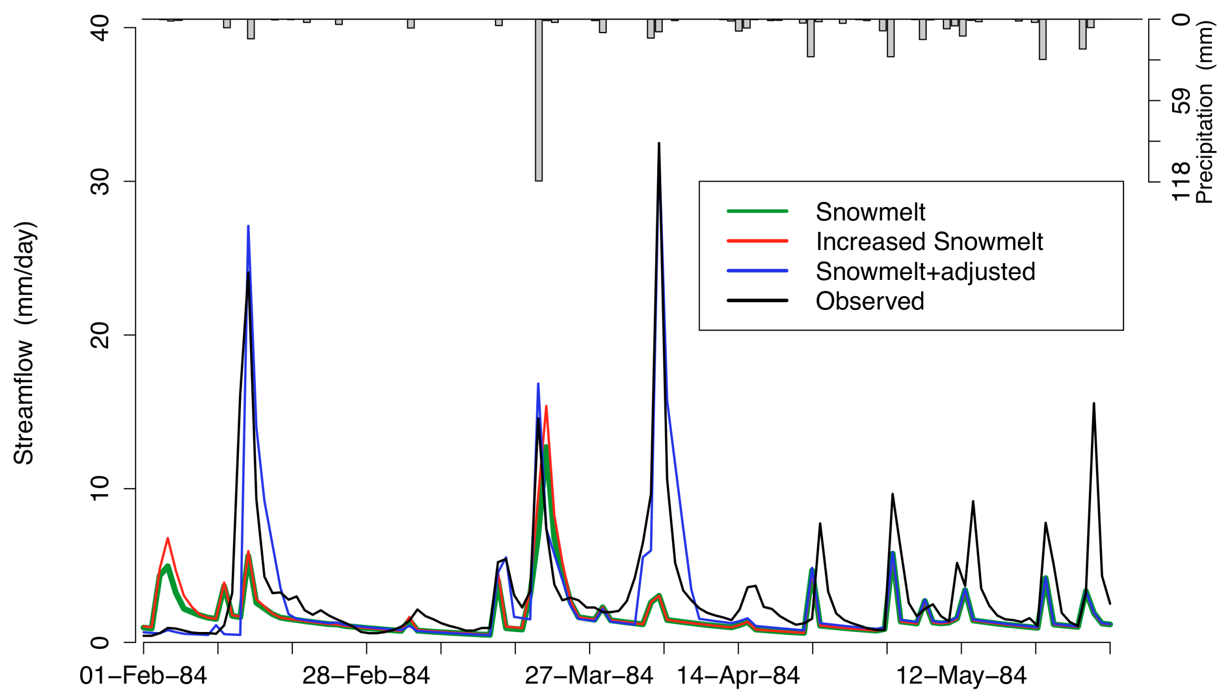


Figure 8. PED Little Tonawanda winter 1984

Black Creek

Daily NSE values for Black Creek were a little better than Little Tonawanda. All metrics can be found in Table 11. Similar to Little Tonawanda Creek, the dataset that yielded the best metrics with the PED model was the snowmelt+adjusted (NSE=0.71). Conversely, the snowmelt and increased snowmelt datasets with SWAT were more representative. PED r^2 for the calibration period was highest at 0.73 for the snowmelt-adjusted dataset and lowest for the other two datasets (0.64). In comparison to Little Tonawanda Creek that had a concentration of low flow values, Black Creek had a wider range of flow values. This could have contributed to better characterization of the watershed, as the model was able to calibrate over a wider range of flows as opposed to a set concentrated on the lower end of the range.

Table 11. SWAT and PED model metrics for Black Creek

	SWAT	PED
Nash Sutcliffe Efficiency		
Snowmelt	0.4	0.63
Increased Snowmelt	0.4	0.63
Snowmelt+adjusted	0.36	0.71
Percent Bias		
Snowmelt	-46	-10.5
Increased Snowmelt	-46	-10.5
Snowmelt+adjusted	-45	-10.7
R^2		
Snowmelt	0.49	0.64
Increased Snowmelt	0.49	0.64
Snowmelt+adjusted	0.45	0.73

Simulated and observed hydrographs for Black Creek can be found in Figure 9 and Figure 10. SWAT predicted flows were consistently lower than observed except for 3 events in January 1981, March 1982 and March 1983 where SWAT over predicted outflow. Hydrographs for all simulation years as well as a hydrograph for 1982 can be found in A. 5 and A. 6 for SWAT, A. 7 and A. 8 for PED.

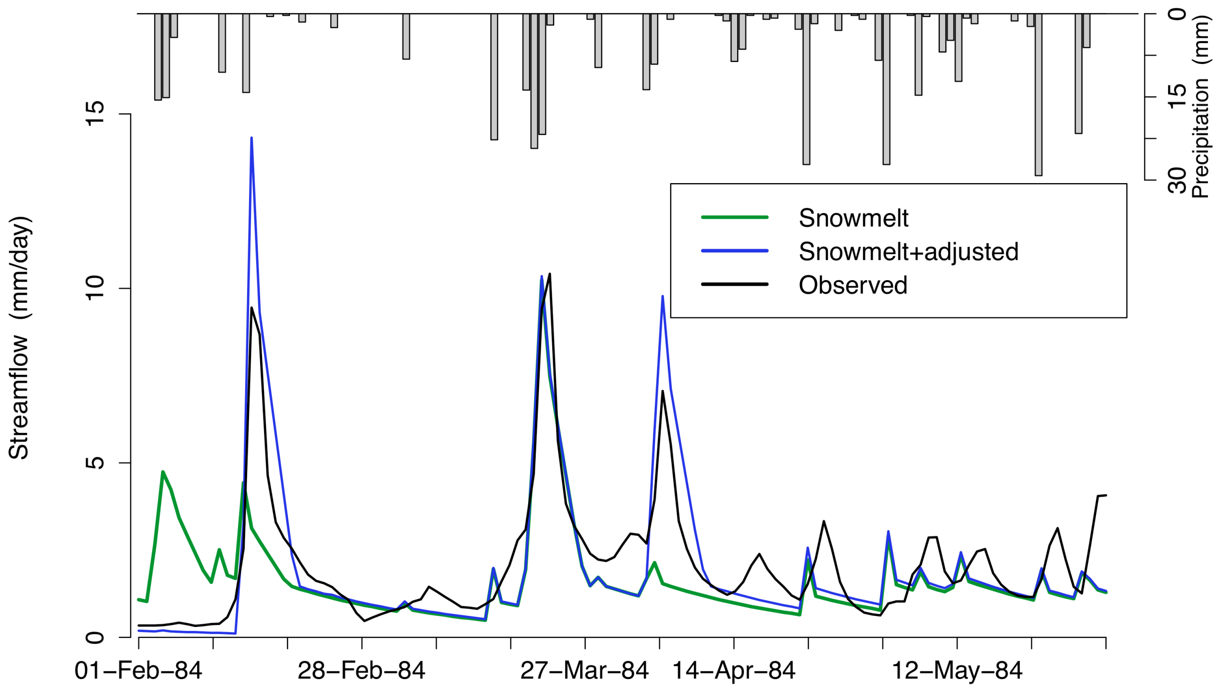


Figure 9. PED Black Creek hydrograph for winter 1984

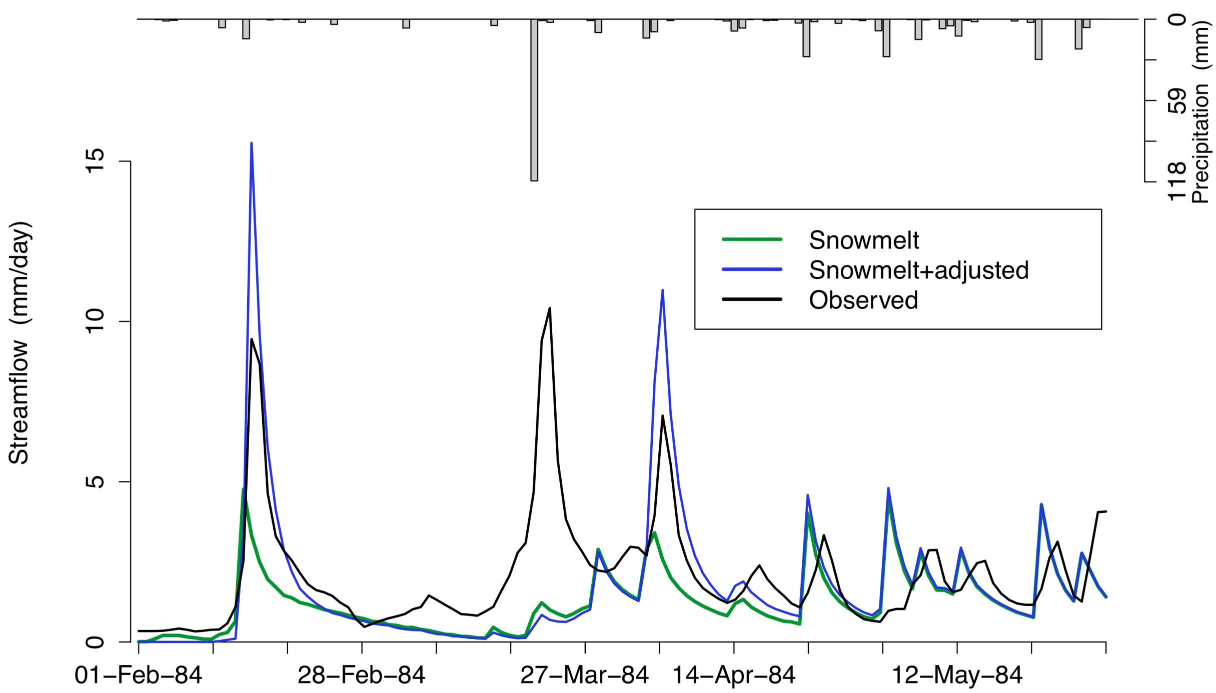


Figure 10. SWAT Black Creek winter 1984

Validation

Validation was conducted on both models with each of the three precipitation series for 1985-1986. Hydrographs for the full validation period were difficult to read so only one year (1985) is presented in the text. Full validation hydrographs can be found in A. 9 and A. 10 for the PED model A. 11 and A. 12 for SWAT.

Little Tonawanda

Model metrics for Little Tonawanda improved for the PED model but declined for SWAT (Table 12). NSE for snowmelt+adjusted was 0.79 for validation and only 0.62 during the calibration time period. The SWAT model performed the best with the increased snowmelt dataset at 0.51, an increase from 0.4. The highest NSE for calibration was achieved by the snowmelt+adjusted dataset at 0.55. Percent bias was better for the PED model with the lowest at -2.9%. This is greatly contrasted with the lowest for the SWAT model at 36.2%. R^2 values were also much better for PED although the SWAT model performed reasonably well.

Table 12. Validation metrics for Little Tonawanda

	SWAT	PED
Nash Sutcliffe Efficiency		
Snowmelt	0.19	0.56
Increased Snowmelt	0.51	0.61
Snowmelt+adjusted	0.47	0.79
Percent Bias		
Snowmelt	-53.3	-25.5
Increased Snowmelt	-36.2	-2.9
Snowmelt+adjusted	-38.7	-9
R^2		
Snowmelt	0.33	0.58
Increased Snowmelt	0.55	0.68
Snowmelt+adjusted	0.56	0.79

Hydrographs for one representative validation year can be found in Figure 11and Figure 12 for Little Tonawanda Creek. The PED model captured peak flows and smaller events better than SWAT. This is especially apparent during December of 1985.

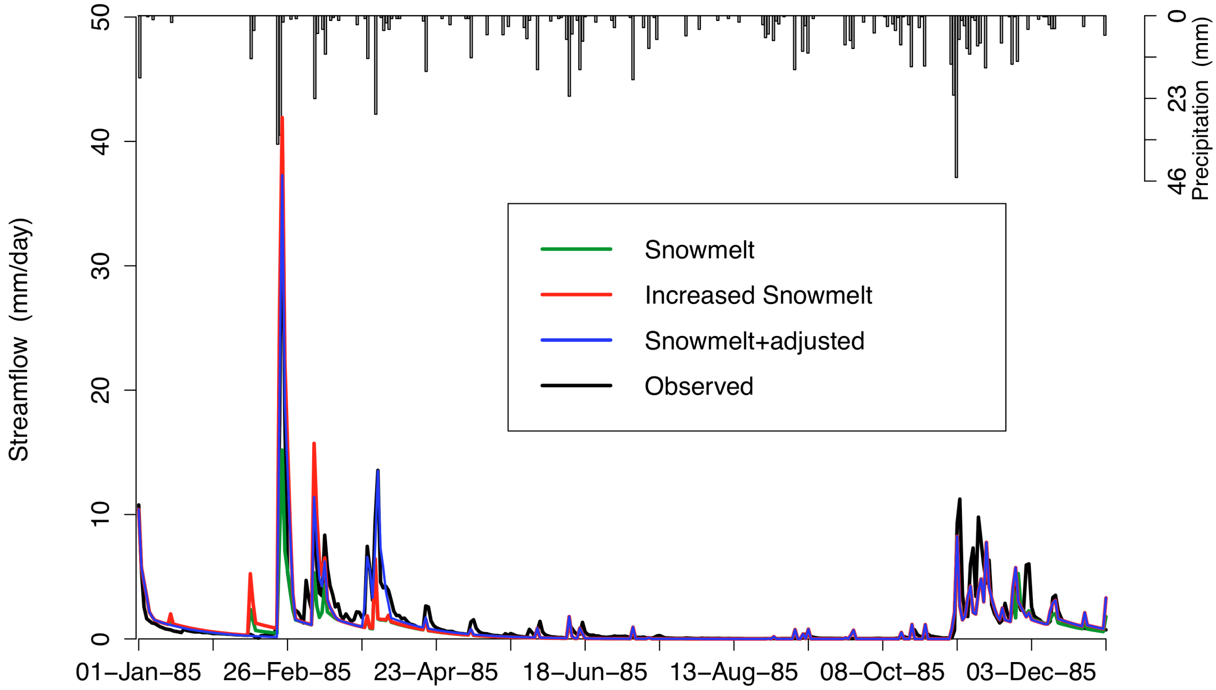


Figure 11. PED Little Tonawanda validation hydrograph

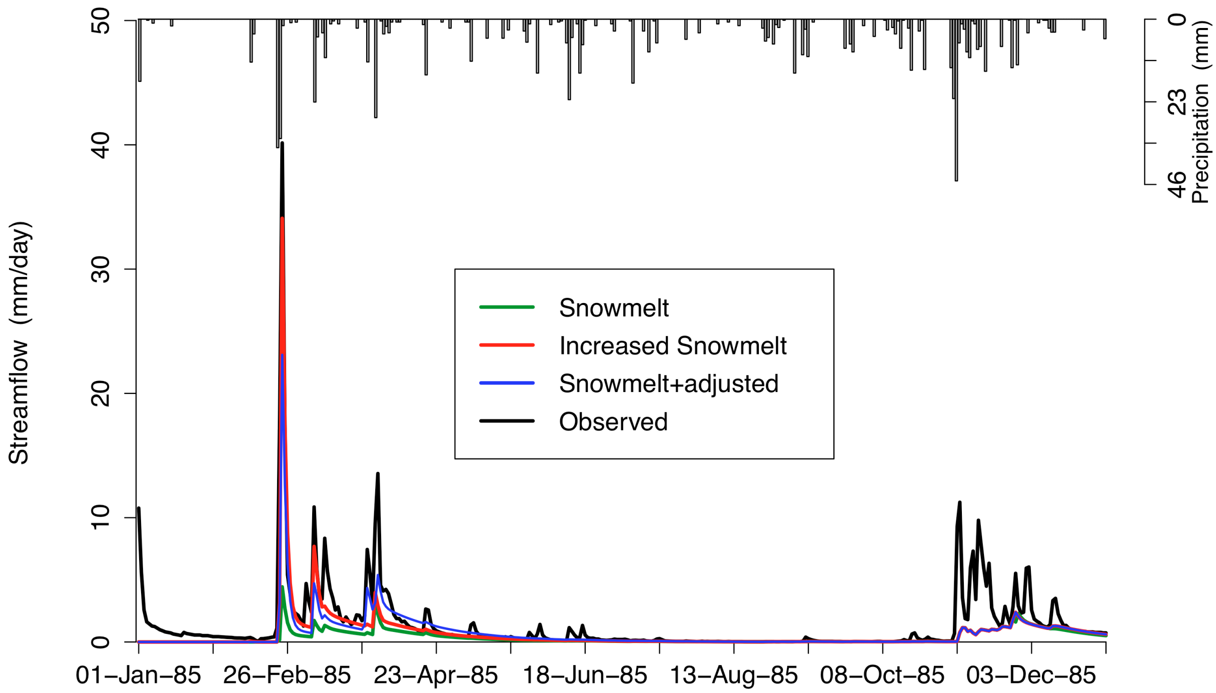


Figure 12. SWAT Little Tonawanda validation years

Black Creek

The validation period for Black Creek behaved similarly to Little Tonawanda in that the PED model saw better model metrics while SWAT model metrics deteriorated. The highest PED NSE achieved during validation was 0.77 which is better than calibration, the highest being 0.71. SWAT saw a decline in NSE from 0.4 being the highest during calibration to 0.26 as the highest for validation. Percent bias was better for PED as well as r^2.

Table 13. Black Creek model metrics for validation years

	SWAT	PED
Nash Sutcliffe Efficiency		
Snowmelt	0.16	0.64
Increased Snowmelt	0.26	0.67
Snowmelt+adjusted	0.24	0.77
Percent Bias		
Snowmelt	-62.1	-23.2
Increased Snowmelt	-57.7	-13.9
Snowmelt+adjusted	-60.9	-14.8
R^2		
Snowmelt	0.35	0.79
Increased Snowmelt	0.44	0.71
Snowmelt+adjusted	0.47	0.79

The PED model captured event flows better than SWAT (see Figure 13 and Figure 14). Variation of flow prediction was minimal across datasets for the PED model. Employing multiple precipitation datasets was more significant for SWAT where the separation of lines is more visible.

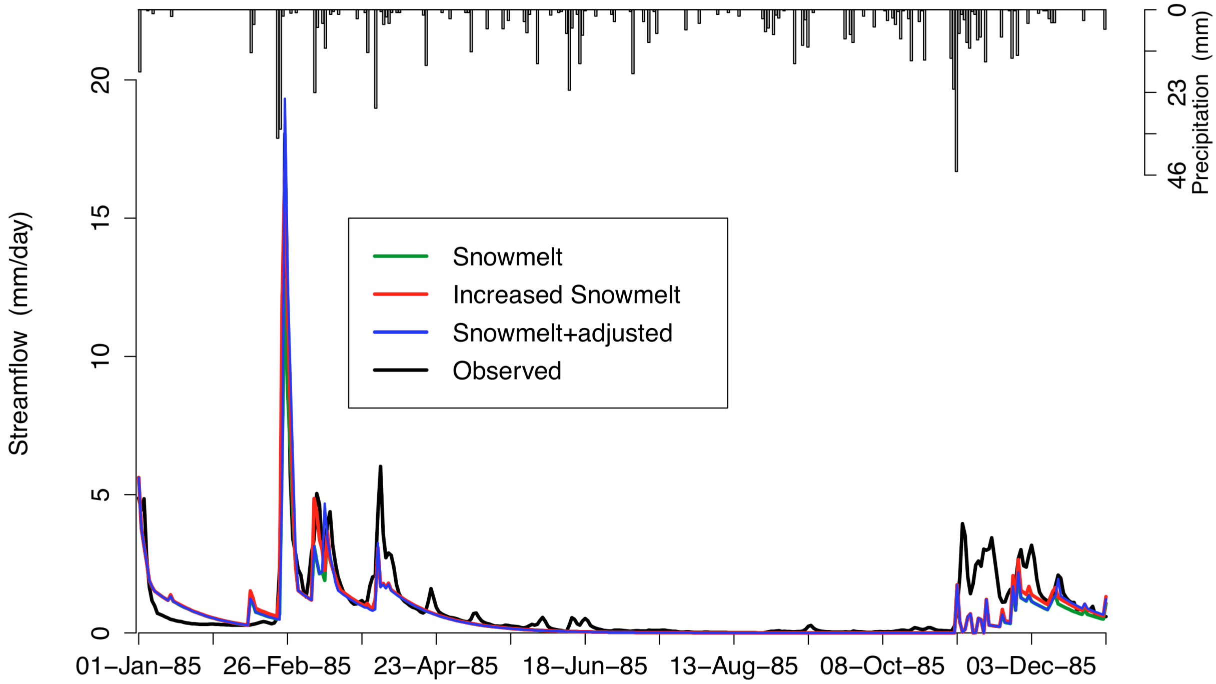


Figure 13. Black Creek PED validation hydrograph for 1985

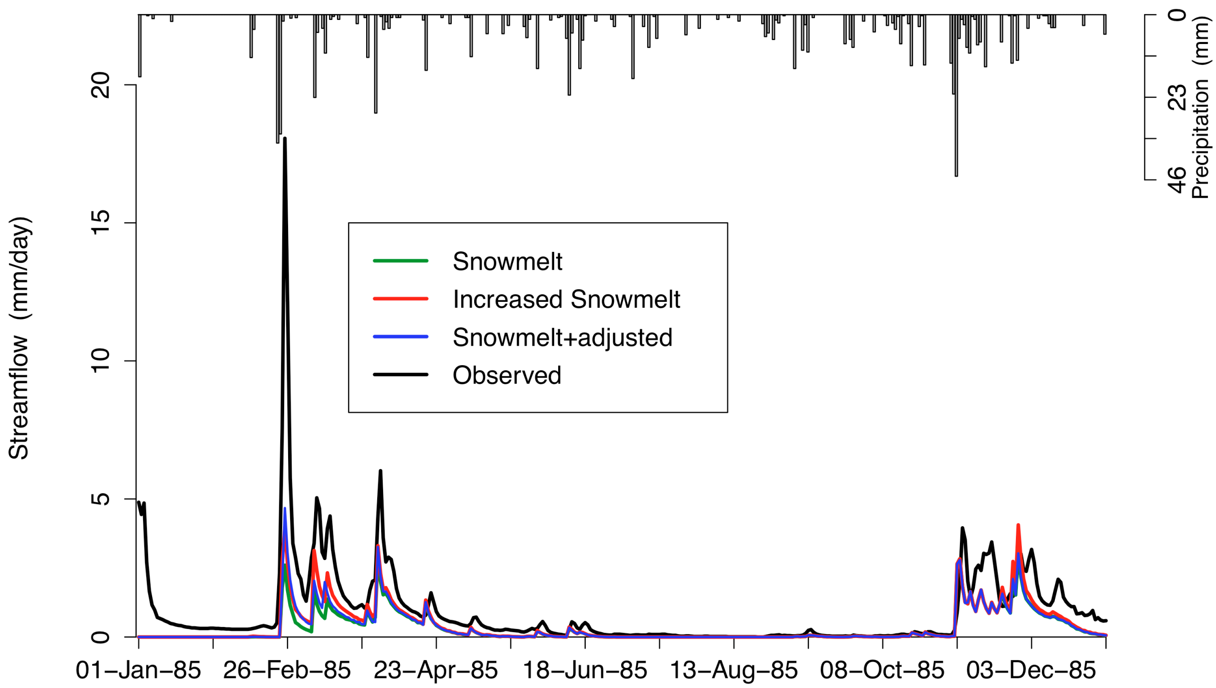


Figure 14. SWAT Black Creek validation hydrograph for 1985.

Simulated Flow from TI Classes

Runoff, interflow and groundwater flow for each TI class were partitioned for analysis for model runs with the snowmelt+adjusted dataset. In Figure 15, the average monthly runoff from 1981-1984 shows that the majority of runoff is coming from higher TI classes. The lower three classes rarely produced runoff during the time period.

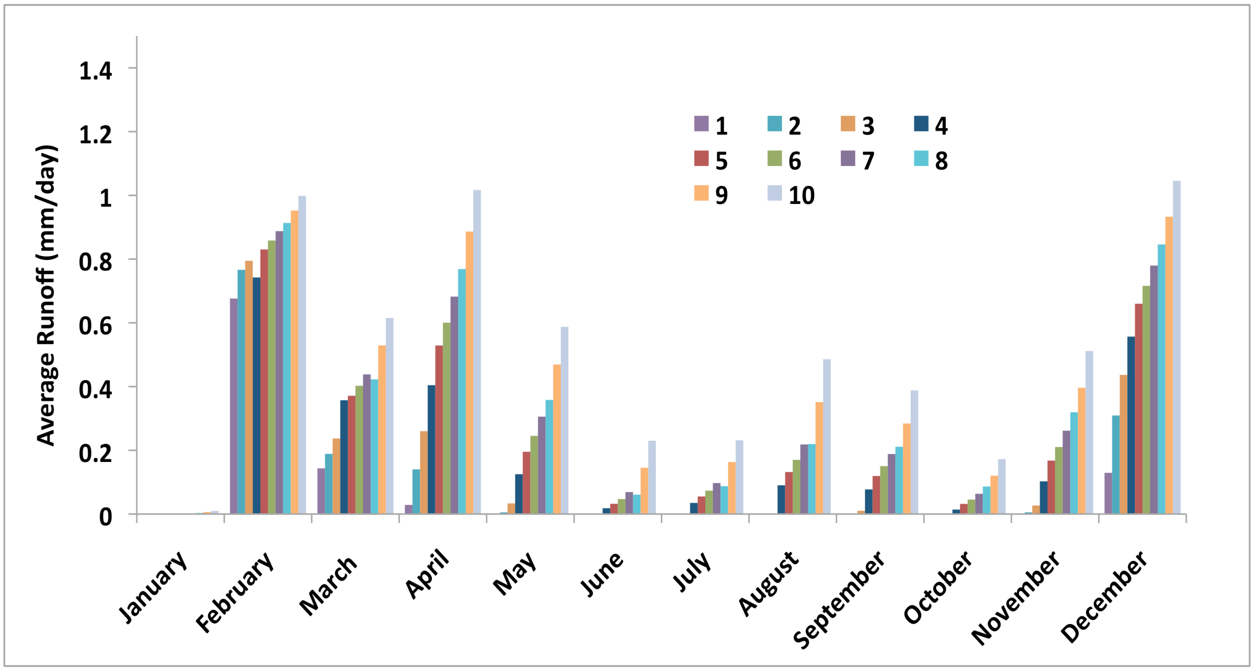


Figure 15. Little Tonawanda average monthly runoff from each TI class.

As expected, groundwater flow from higher TI classes would be lower as precipitation is leaving these areas as runoff instead of infiltrating (A. 17). Mid-range and lower TI classes produced the most groundwater. Summer months did not show a large distinction between classes unlike fall, spring and winter months. This is expected, though, as there is generally less precipitation during the summer.

A significant difference between TI classes can be seen in interflow generated (Figure 16). Higher and mid-range TI classes produced much less interflow in comparison to lower TI classes. Average interflow for mid-range and upper TI classes did not change much through the year while average interflow for lower TI classes fluctuated.

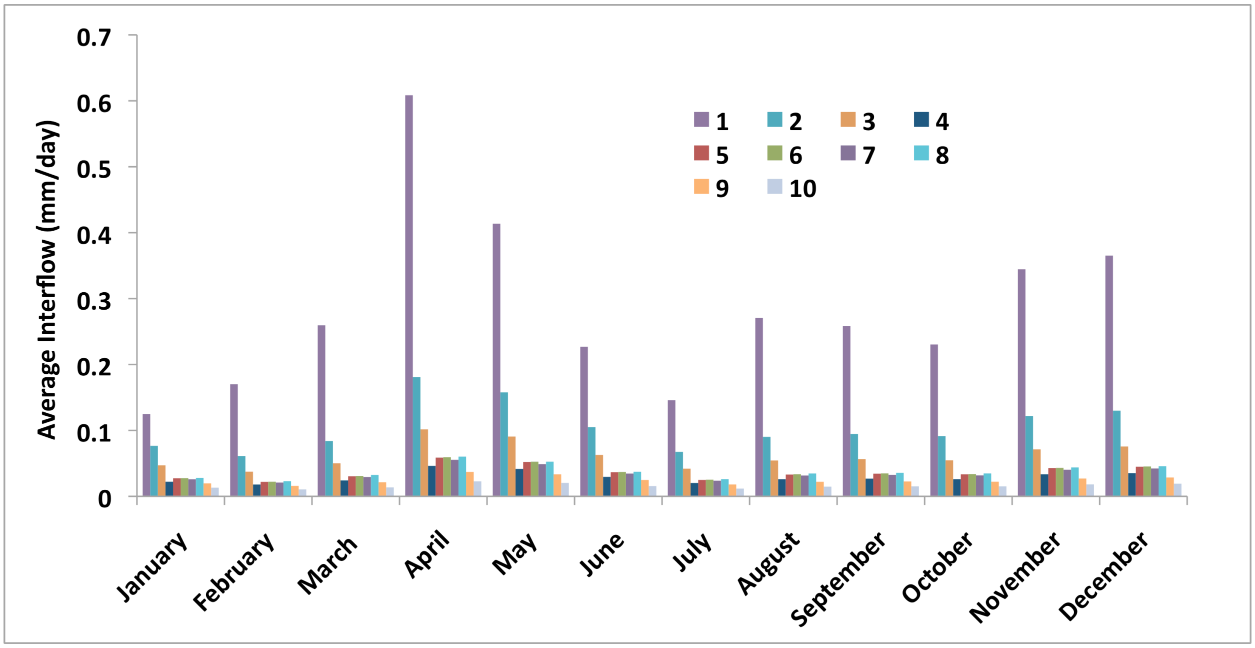


Figure 16. Little Tonawanda average monthly interflow for each TI class from 1981-1984

In A. 18, the average monthly runoff from 1981-1984 for Black Creek can be seen. In general, higher TI classes produced significantly more runoff than lower and mid-range TI classes. The lowest TI classes produced minimal runoff, with the exception of February, while mid-range TI classes did not produce runoff during summer months. Higher TI classes produced the largest portion of runoff over the simulation period.

In contrast to expected response, SWAT simulated groundwater flow from higher TI classes was greater than other classes (Figure 17). The lowest TI classes produced very little groundwater flow while mid-range TI classes produced some groundwater flow. As a percentage of the total amount of flow entering the area, the amount leaving as groundwater is very small.

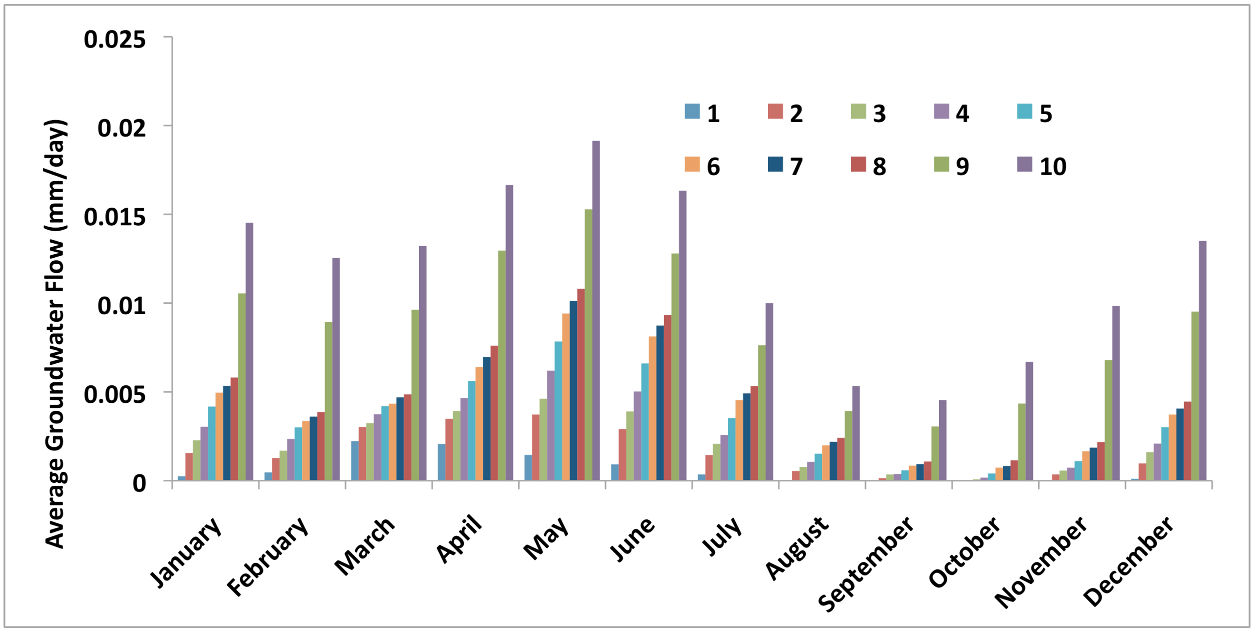


Figure 17. Black Creek average monthly groundwater flow for each TI class

Interflow for Black Creek was mainly from the lowest TI classes but received some contribution from mid-range TI classes and higher TI classes during winter and spring (Figure 18). Almost no interflow was produced from July to September.

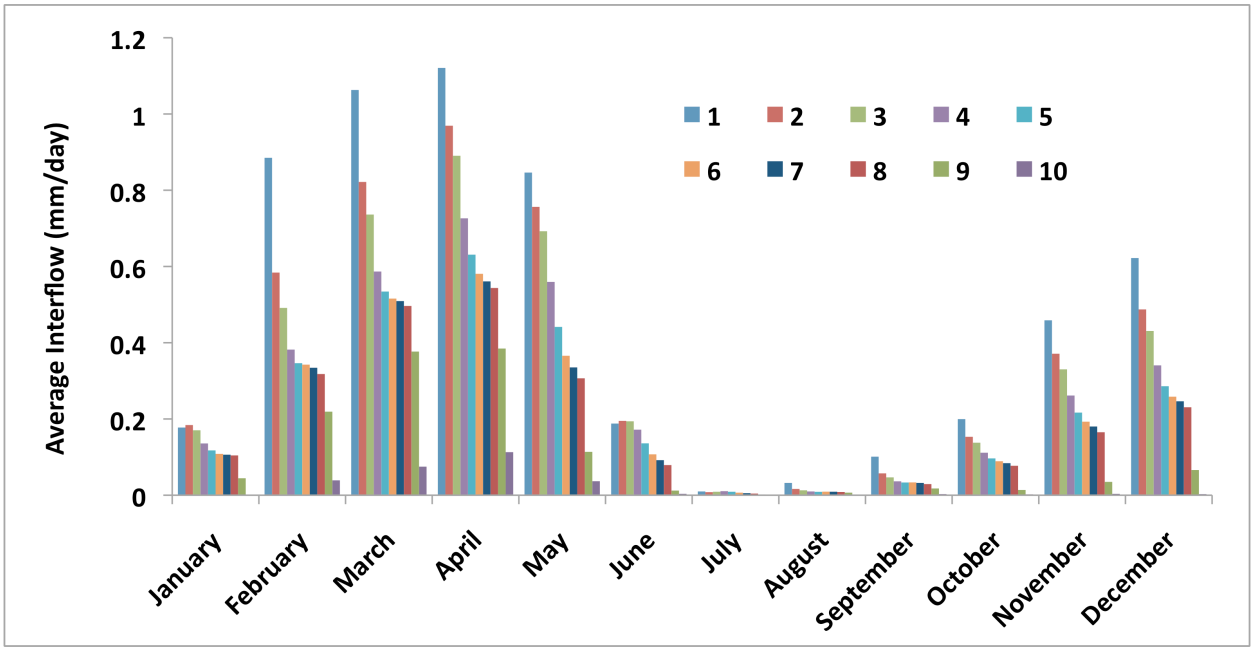


Figure 18 Black Creek average monthly interflow for each TI class from 1981-1984

To determine where each TI class was distributing water across the year (either storage or outflow from groundwater, interflow or runoff), the amount of outflow and storage were compared against the total amount of precipitation. Storages as a fraction of the net precipitation (net precipitation = actual precipitation – evapotranspiration) for Little Tonawanda Creek can be found in Figure 19. June and July were the only months that showed a storage deficit while all other months were storing water. Higher TI classes stored less water in comparison to lower TI classes for all months but the difference was not significant. This is a result of most of the water exiting the TI class immediately via runoff and not entering into groundwater or interflow that releases water more slowly. Overall, SWAT predicted a 27% loss of water in the watershed.

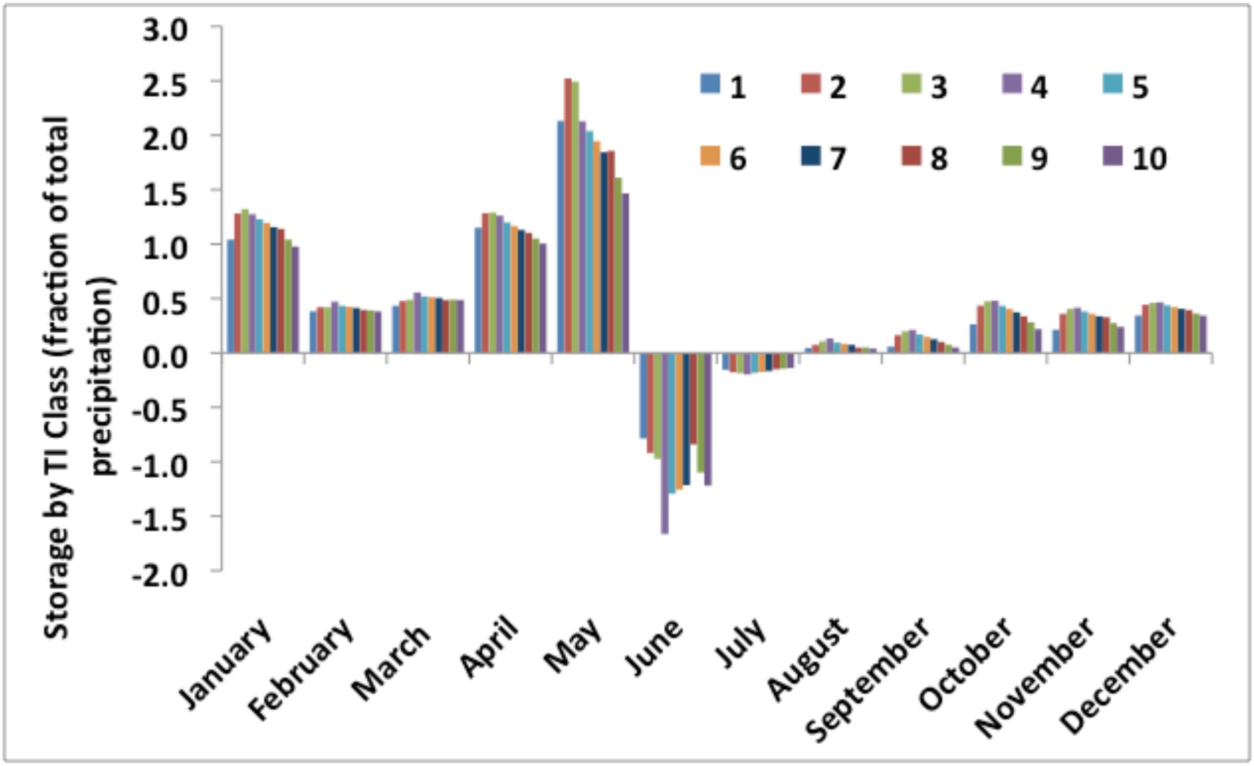


Figure 19. Little Tonawanda average storage in soil as fraction of precipitation minus evaporation by TI class averaged over 1981-1984.

Black Creek TI classes demonstrated similar periods of surpluses and deficits but in much smaller fractions than Little Tonawanda Creek (Figure 20). Higher TI classes generally stored more water in comparison to mid and lower TI classes. Months of storage deficits were June and July while September-December showed little contribution to water storage.

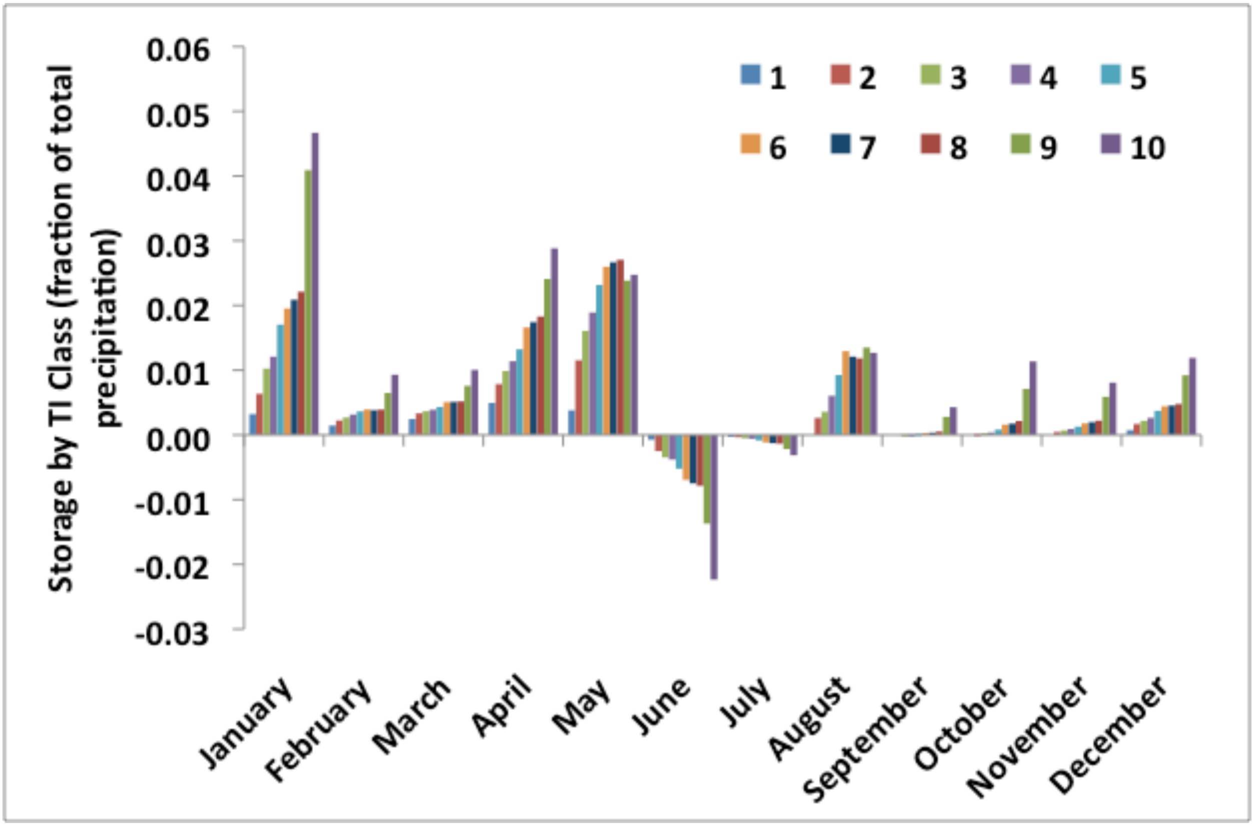


Figure 20. Black Creek storage in groundwater and deep aquifer from TI class as percentage of precipitation-evaporation averaged monthly from 1981-1984

Flow partitioning in the PED model was similar to SWAT. Groundwater flow was dominant in the Little Tonawanda PED model (Figure 21) and the SWAT model. Interflow only occurred during months with more precipitation (January-April and November-December). Runoff consistently contributed during all months.

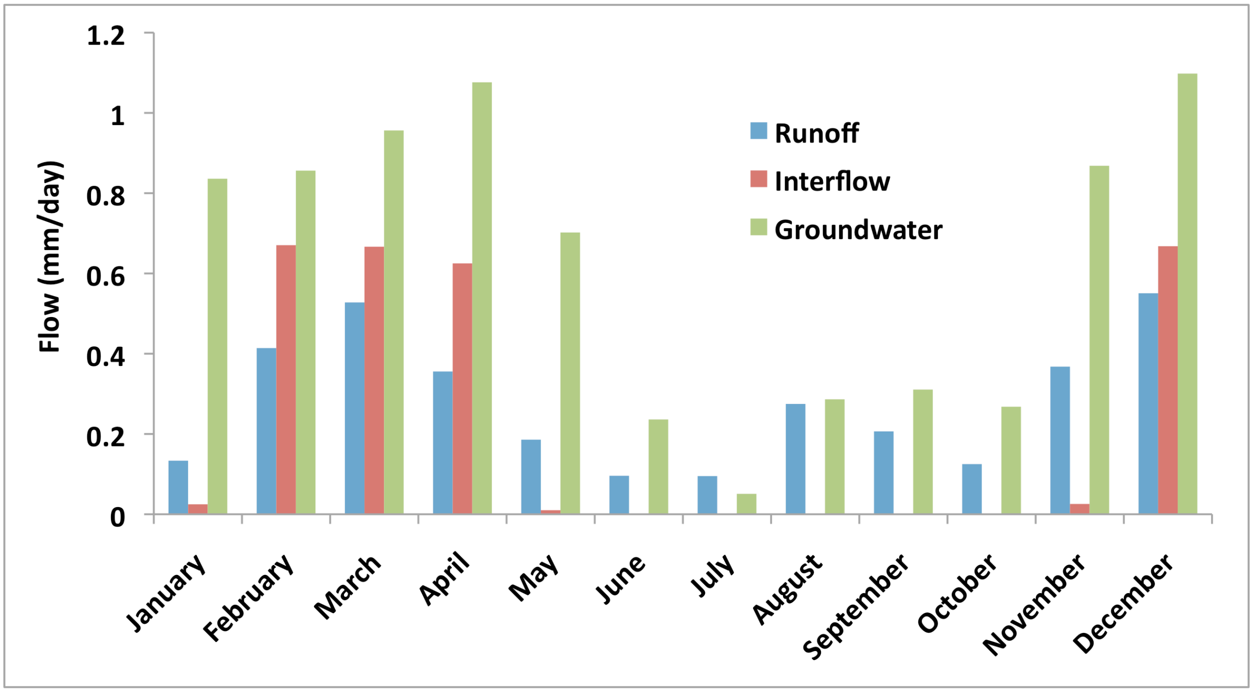


Figure 21. PED flow partitioning for Little Tonawanda Creek averaged monthly for 1981-1984

Groundwater was also dominant for Black Creek (Figure 22). This is in contrast to the SWAT model that predicted less groundwater flow and more interflow. The PED model produced little interflow and even less runoff across all months.

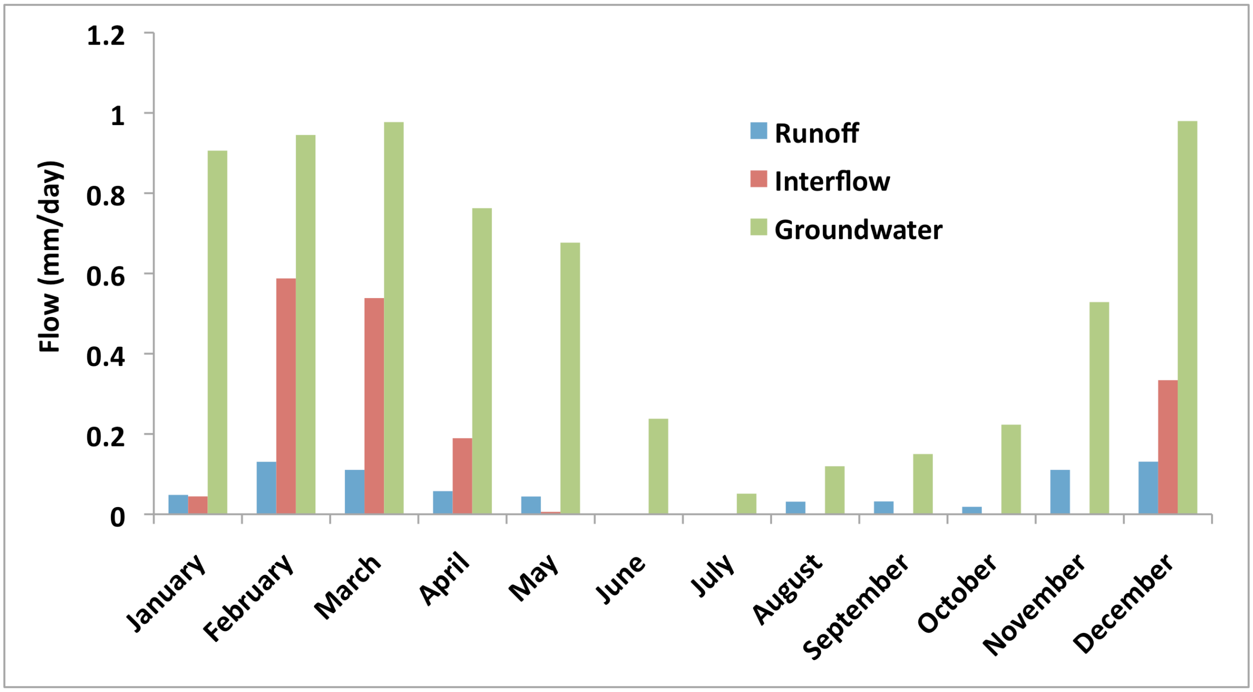


Figure 22. PED flow partitioning for Black Creek averaged monthly from 1981-1984.

Discussion

Incorporating the snowmelt+adjusted dataset improved the timing and magnitude of melt events in the PED and SWAT models with the exception of the Black Creek SWAT model where metrics declined slightly. In the snowmelt+adjusted dataset, values from the snowmelt models were adjusted to better correspond to flows as precipitation and flows are reported at different intervals. This change in the input improved representation of events.

Increasing snowmelt on a per event basis did not improve SWAT model or PED model predictions for Black Creek however it did improve predictions for Little Tonawanda Creek. More snow could be falling in Little Tonawanda due to its higher average elevation in comparison to Black Creek. Although the two watersheds are adjacent to each other, the mid and lower portions of Black Creek are at lower elevations. The Little Tonawanda watershed could be receiving more snowfall due to its higher elevation in comparison to Black Creek.

Moriasi et al. (2007) suggested that satisfactory model metric values for NSE, percent bias and r^2 are >0.5, +/- 25% and >0.5, respectively. Model representation will be judged using these criteria.

Hydrographs for the models with the highest NSE (snowmelt+adjusted datasets PED NSE=0.62 and SWAT NSE=0.55) for Little Tonawanda Creek can be found in Figure 23. Both models capture the largest flow peaks but the PED model captures smaller events better. Groundwater flow is higher for SWAT and can be seen by the length of time it takes for peak flows to recede. It is most apparent here that the PED model of Little Tonawanda Creek is more representative.

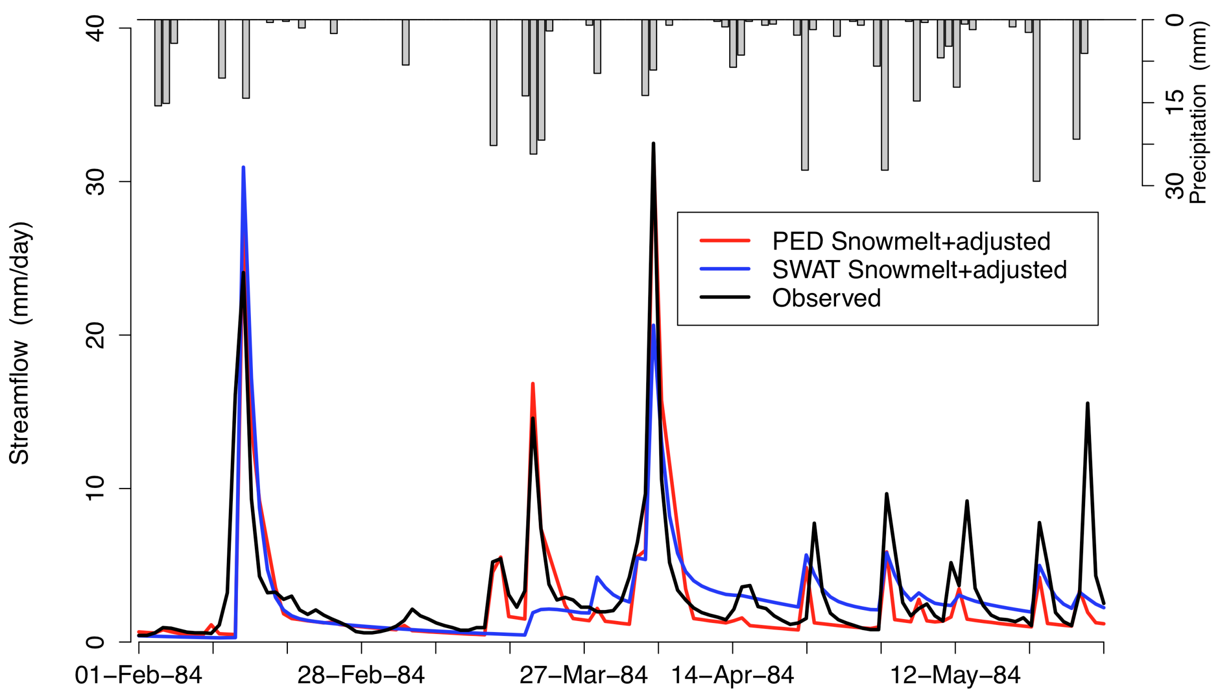


Figure 23. PED and SWAT model predictions with highest NSE for Little Tonawanda Creek for 1984

The models with the highest NSE (PED snowmelt+adjusted NSE=0.71, SWAT snowmelt NSE=0.4) for Black Creek can be found in Figure 24. The PED model was able to capture peak flows better while both models simulated smaller event flows well. SWAT consistently under predicted flows more so than the PED model but would over predict for smaller events.

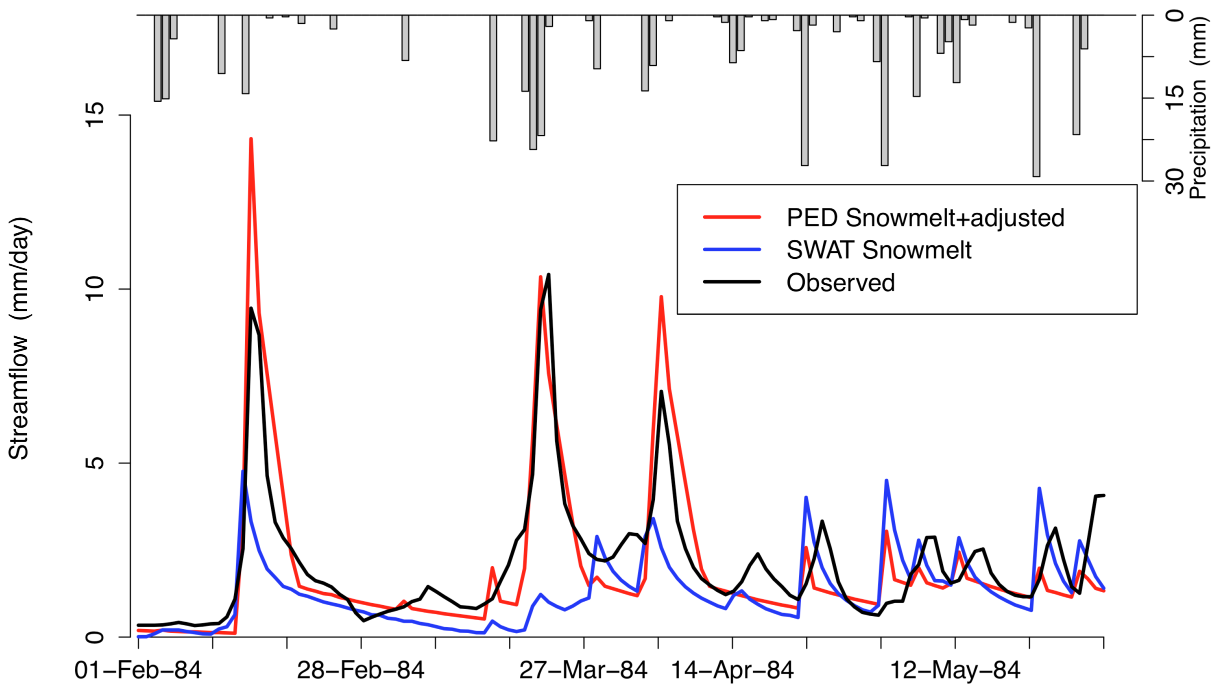


Figure 24. SWAT and PED model prediction for most representative sets for 1984.

It is interesting that the validation period metrics improved for the PED model but declined for the SWAT model. For Little Tonawanda Creek the validation period for PED yielded a NSE of 0.79 with the snowmelt+adjusted dataset, which is significantly above the calibration period NSE of 0.62. The Black Creek model had similar results as the validation period had a NSE of 0.77. SWAT validations were reasonable for Little Tonawanda Creek but poor for Black Creek with the highest NSE being 0.26. In light of the metrics for the validation period, the PED model can achieve better future predictions over the SWAT model for these watersheds.

Runoff in SWAT is modeled using the SCS-CN equation where the main parameter influencing runoff is the curve number. The curve number in our application was based on landscape position. As expected, higher TI classes with higher curve numbers produced more runoff. The relative amount of runoff produced is also significant during periods of more intense storm events where higher TI classes produced much more runoff than lower TI classes. This is particularly noticeable for Black Creek where average monthly runoff during the summer months came only from higher TI classes (A. 18). Little Tonawanda produced much more runoff and from a range of TI classes. This could be due to Little Tonawanda having a higher average slope in comparison the Black Creek. Little Tonawanda had a higher average slope of 10% as compared to 2.8% for Black Creek and could have forced lower TI classes to contribute more runoff.

Groundwater flow for Little Tonawanda mainly came from mid-range TI classes (A. 17), though it was not considerably more than lower or upper TI classes. This is in contrast to Black Creek where higher TI classes unexpectedly contributed the most groundwater flow, which could be a result of the model accounting for the Bergen-Byron Swamp. Lower TI classes in Little Tonawanda and Black Creek yielded much more interflow than mid and upper TI classes (Figure 16 and Figure 18). Relatively large interflows from Black Creek were also observed (Figure 18). This is a result of the lower curve numbers routing flow to storage and the water leaving as interflow because the soil is sufficiently saturated to produce interflow. Little Tonawanda had lower AWC making susceptible to producing flow as the soil is more easily saturated. Black Creek had higher threshold to contribute groundwater flows as well a lower "revap" constant (that partitions groundwater back into the upper layer) creating a well-fortified groundwater storage mechanism for Black Creek that forced water to interflow. This prevented water from being stored in the shallow aquifer and forcing it to be steadily discharged via the baseflow recession variable in SWAT. The similarity of the hydrology in the areas should yield similar parameters (with the contribution of slope taken into account) but some difference can be attributed to the Bergen-Byron Swamp dampening flows before the Churchville gage and forcing the model to steadily provide flow from interflow, a compromise in the time lag from runoff and groundwater flow.

The snowmelt+adjusted dataset improved predictions for all models and watersheds with the exception of the Black Creek SWAT model. The hydrograph of both models using this dataset can been found in **Error! Reference source not found.**. Results using other datasets for Black Creek and Little Tonawanda can be found in the Appendix (A. 13, A. 14, A. 15, A. 16). The SWAT model had sharper responses during small event flows. For larger events, SWAT was not consistent in capturing the flow.

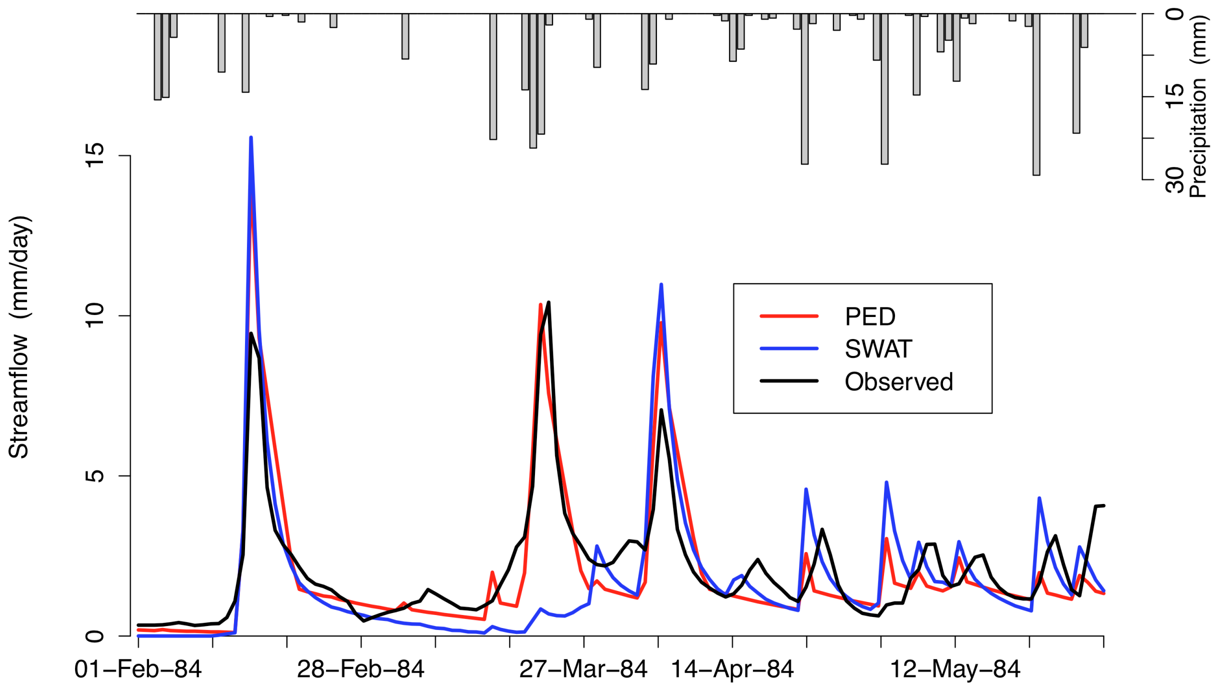


Figure 25 SWAT and PED models for Black Creek using the snowmelt+adjusted dataset for winter 1984

The PED model for Little Tonawanda partitioned flow similar to a lower to mid-range TI class. This is would be consistent with an averaging of all TI classes across that watershed. June to October did not produce any interflow so that the streamflow response was a result of baseflow and the occational storm event. SWAT predicted large amounts of groundwater flow and runoff and very little interflow (and mainly from lower TI classes).

Contrasted with Black Creek, interflow and runoff contributed very little. SWAT predicted that most of the flow to the stream came from interflow and runoff while the PED model predicted that most of the contribution to the stream would come from groundwater. This difference is a result of calibration techniques. For SWAT, the model was calibrated using an optimization program that systematically adjusted parameters to best reproduce stream flow using daily NSE as a measure of how representative the model is. It could have compensated for groundwater flow contributions using interflow. For the PED models, the calibrations were completed by hand so that known contributions from groundwater, as indicated by the shape of the hydrograph, were adequately represented. Interflow flow decreases linearly with time while the log of groundwater decreases linearly with time. Given the small slope of the watershed, the groundwater component is likely more significant than the interflow.

Conclusions

Accurately modeling VSA hydrology is an important tool for mitigating non-point source pollution and providing insight into policy mechanisms to reduce nutrient introduction to water bodies. Black Creek is listed as impaired on the NYSDEC 303(d) list and is a large contributor to pollution at the Rochester embayment of Lake Ontario. It is agriculturally based and located in a region that embodies VSA hydrology. Thus, developing a VSA based model to simulate the impact of different management practices is imperative to help improve water quality in the region.

Although, some mechanisms in SWAT can be externally modified (i.e. by adjusting SWAT's input data) to represent VSA hydrology, internal routing equations prevent the model from realistically accounting for saturated areas in the landscape. Runoff was consistent with VSA hydrology, however, groundwater and interflow were not consistent. Modifying subsurface flow, and interflow in particular, to account for contributions from saturated areas would greatly improve SWAT model predictions.

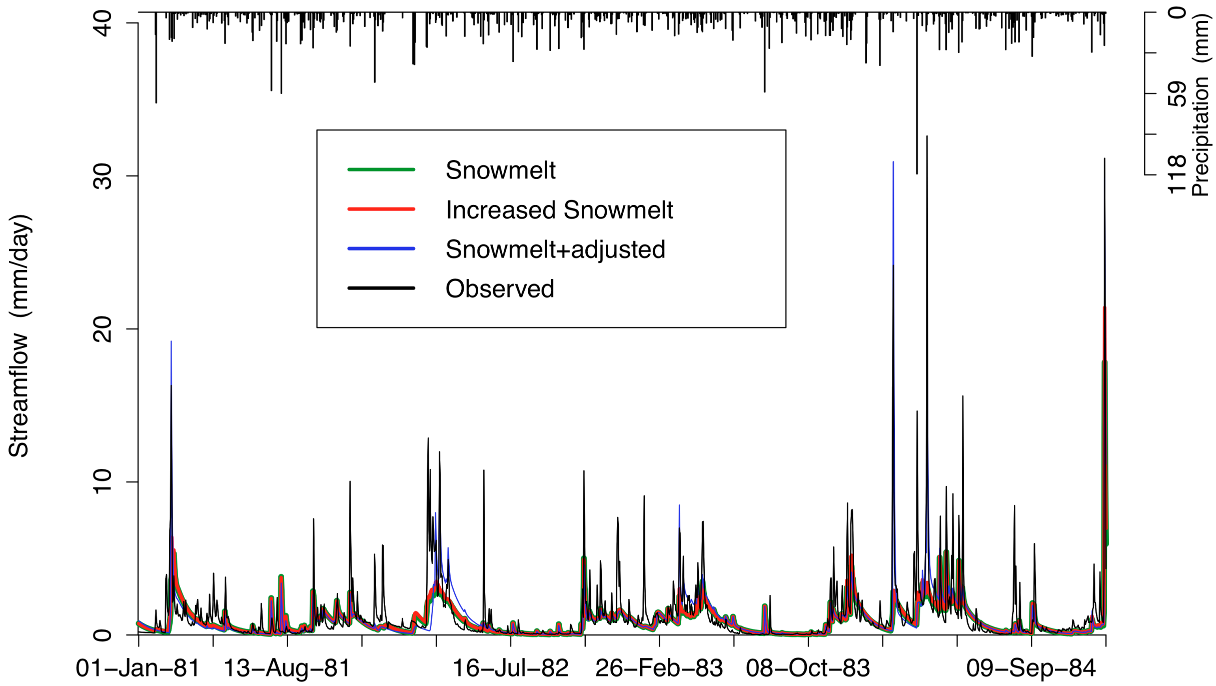
Weak snowmelt modeling is a notable hindrance to accurately modeling snowmelt dependent stream flows. The process-based model used in the study improved predictions but still required manual modifications to capture events accounted for in flow records.

Delineation of TI classes could be adjusted for better representation. In the study, the response of 10 TI classes tended to cluster into 3 major groups. The model could be simplified by reducing the number of TI classes. Additionally, the 10 TI classes were evenly divided for each watershed. A more effective distribution could consist of higher TI classes encompassing a small percentage of the landscape, and lower TI classes covering a larger percentage. Modifying the tool used to delineate these areas could improve model performance and VSA representation.

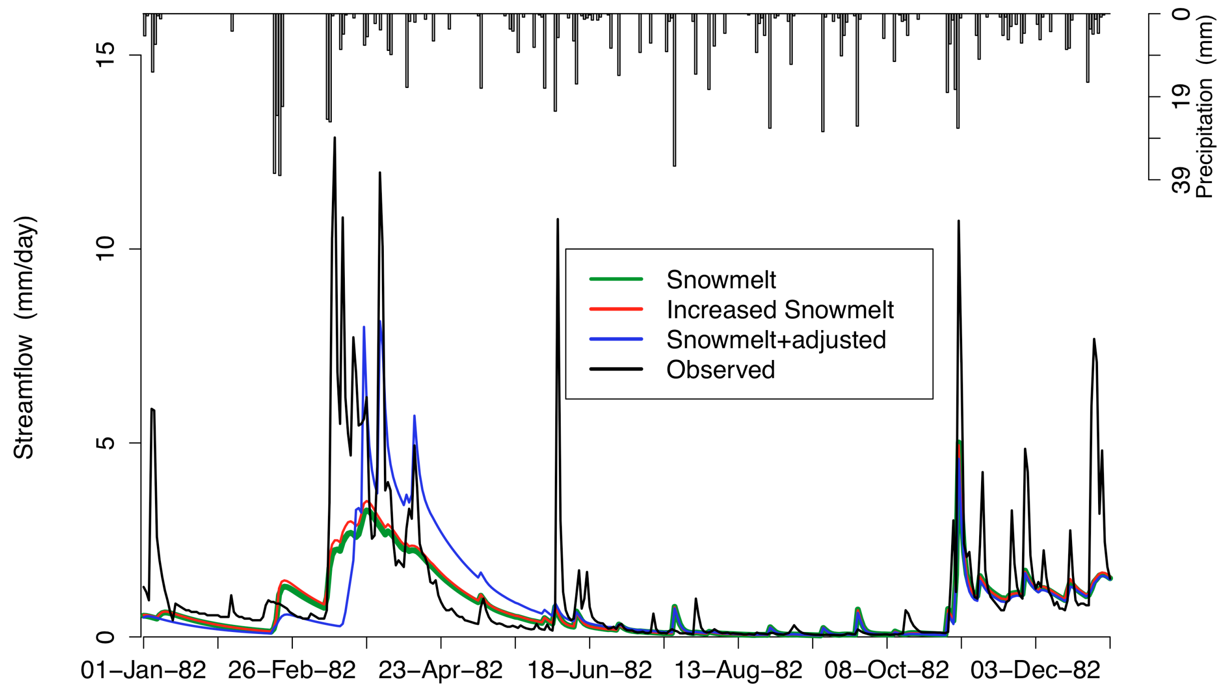
In terms of model metrics, the simple models of Black Creek performed satisfactorily as well as the SWAT model of Little Tonawanda. The Bergen-Byron swamp plays a significant role in modeling and could be more explicitly modeled to improve simulations. The simple model partitioned outflow (groundwater, runoff and interflow) differently than SWAT, which could be due to different calibration techniques used.

Overall the PED model is easier to setup and calibrate and yields comparable results to SWAT. The time, forcing variables and parameters required for SWAT are large and, in terms of efficiency, the simple, VSA based model is better. If the model is to be used to predict flows outside the calibration time period, this study suggests that the PED model would be more accurate than SWAT.

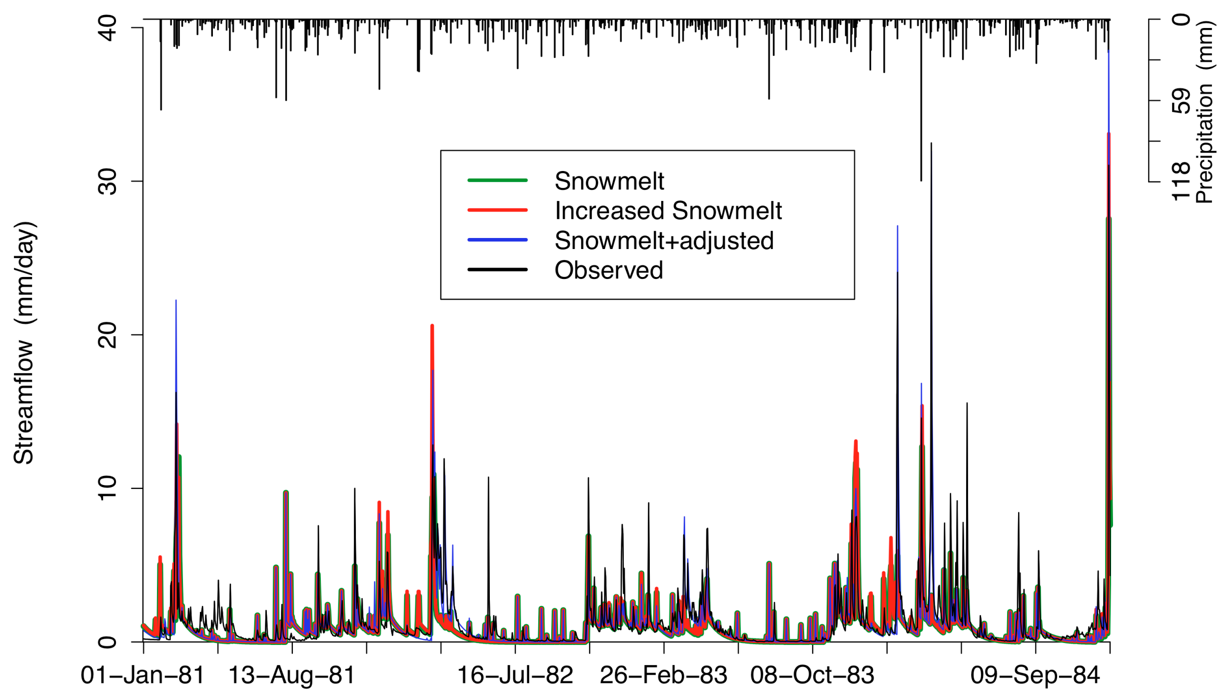
Appendix



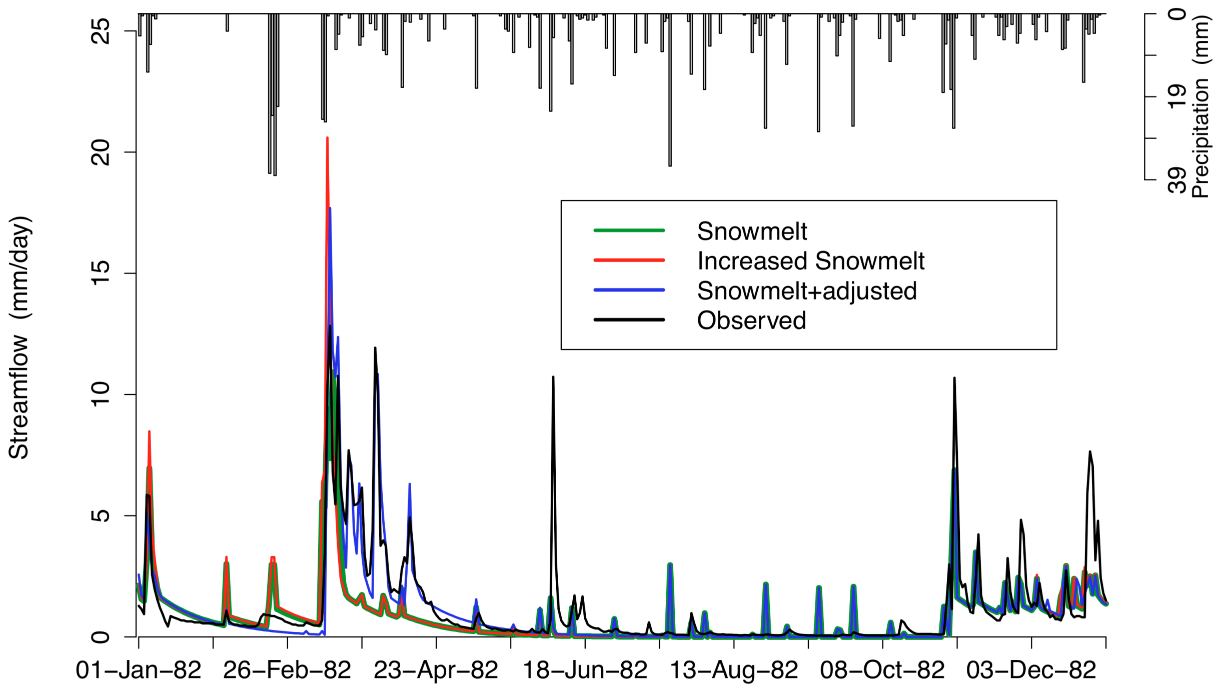
A. 1 SWAT Little Tonawanda hydrograph of all calibration years



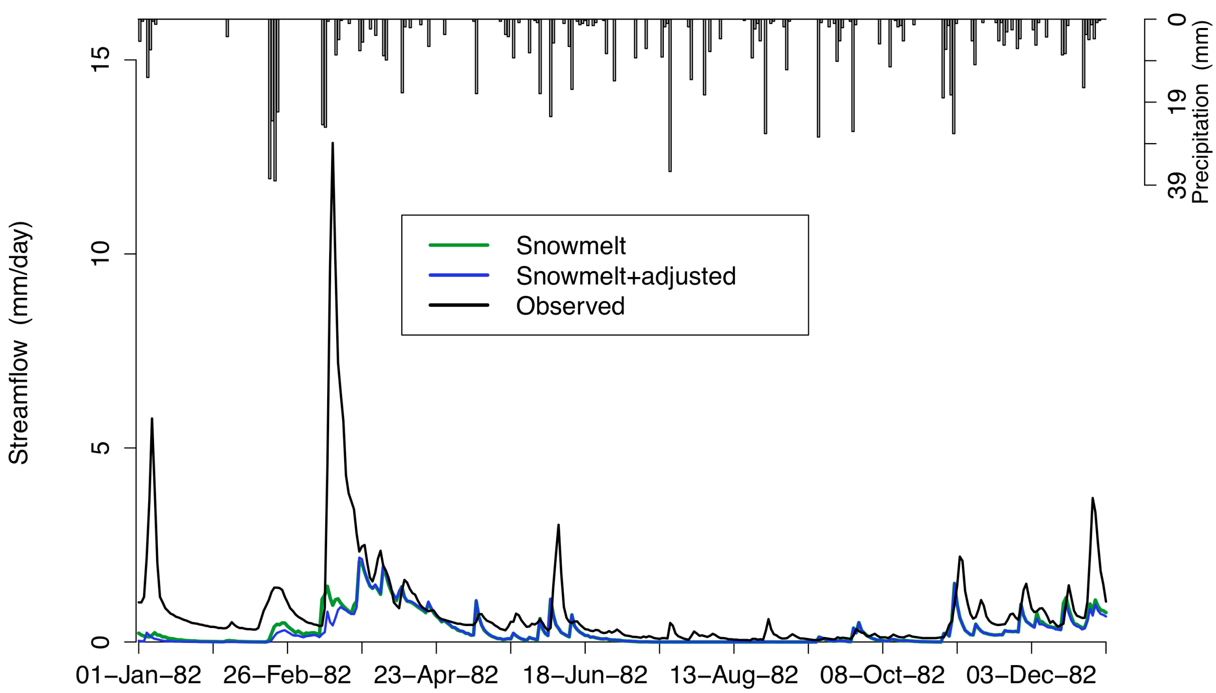
A. 2 SWAT Little Tonawanda hydrograph of 1982



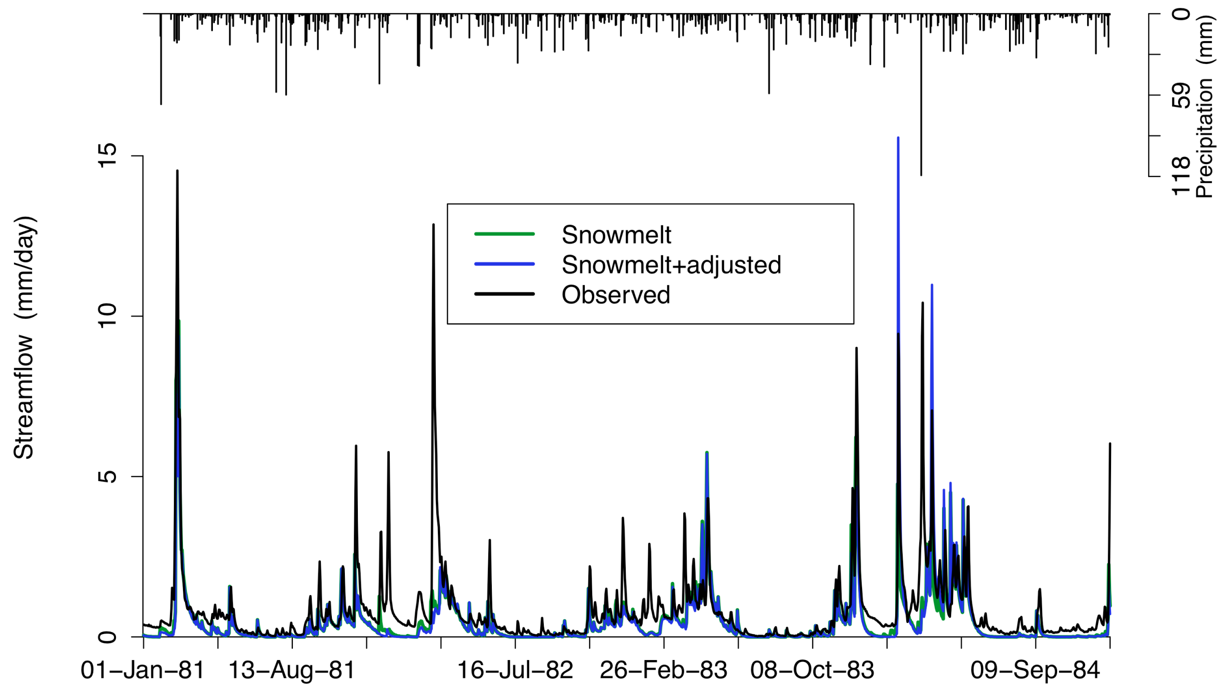
A. 3 PED Little Tonawanda hydrograph for all years



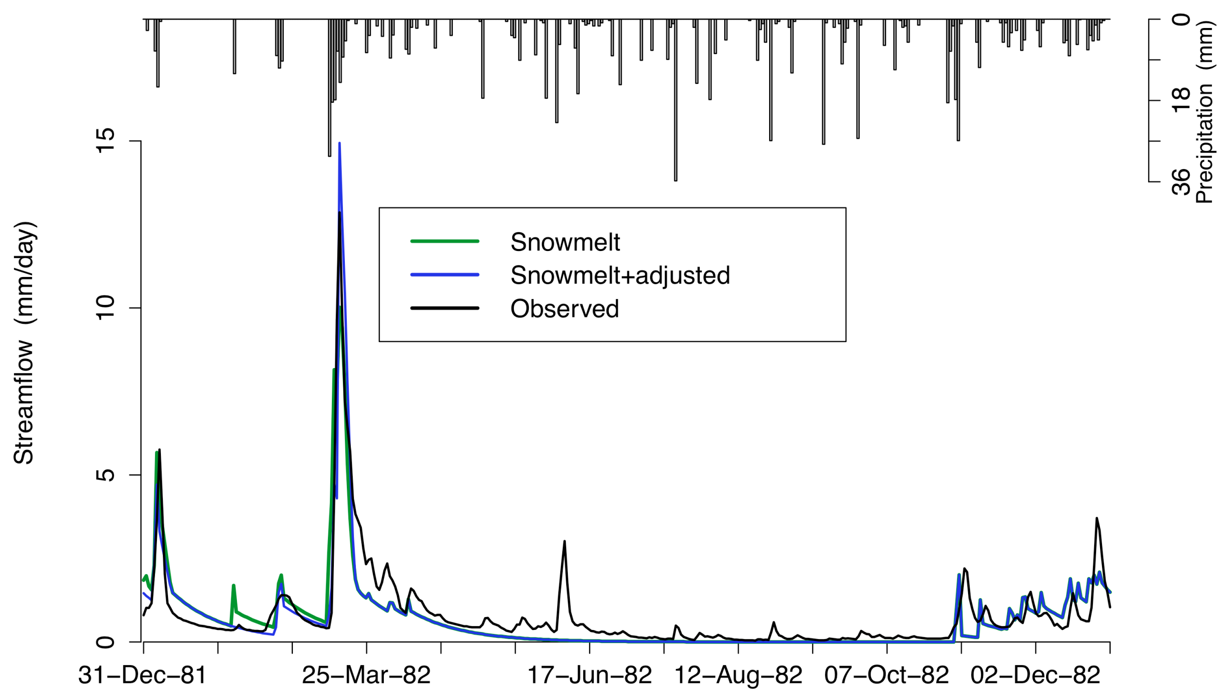
A. 4 PED Little Tonawanda hydrograph of 1982



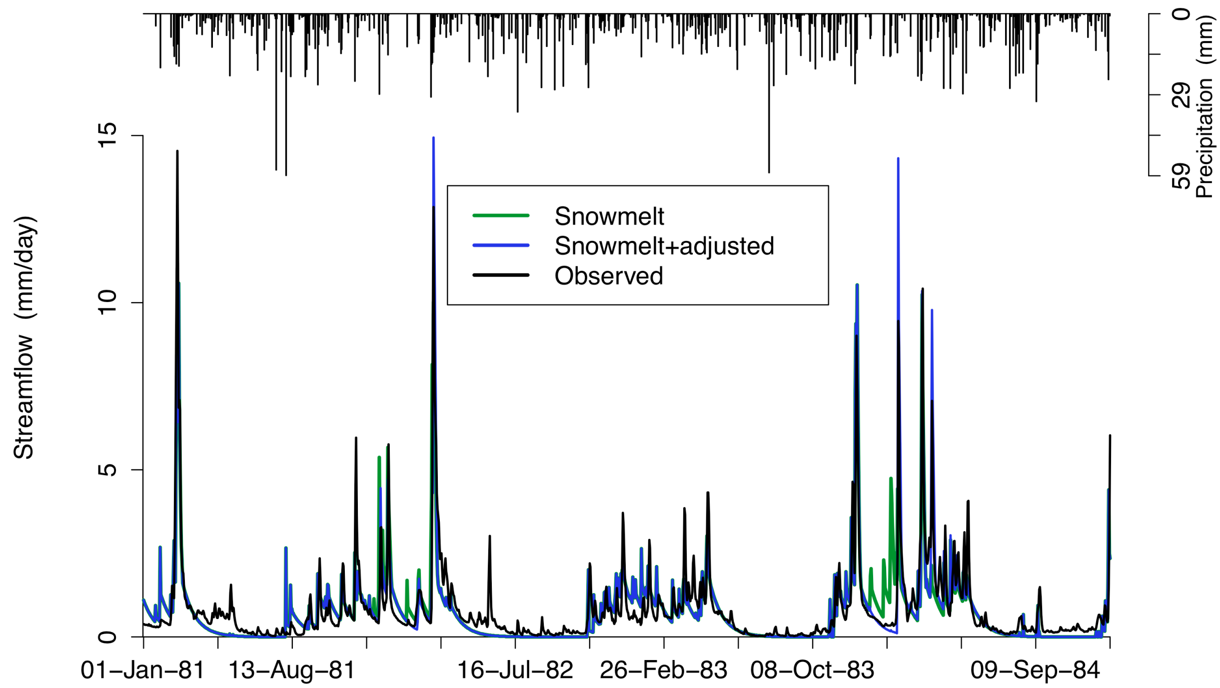
A. 5 SWAT Black Creek hydrograph for 1982



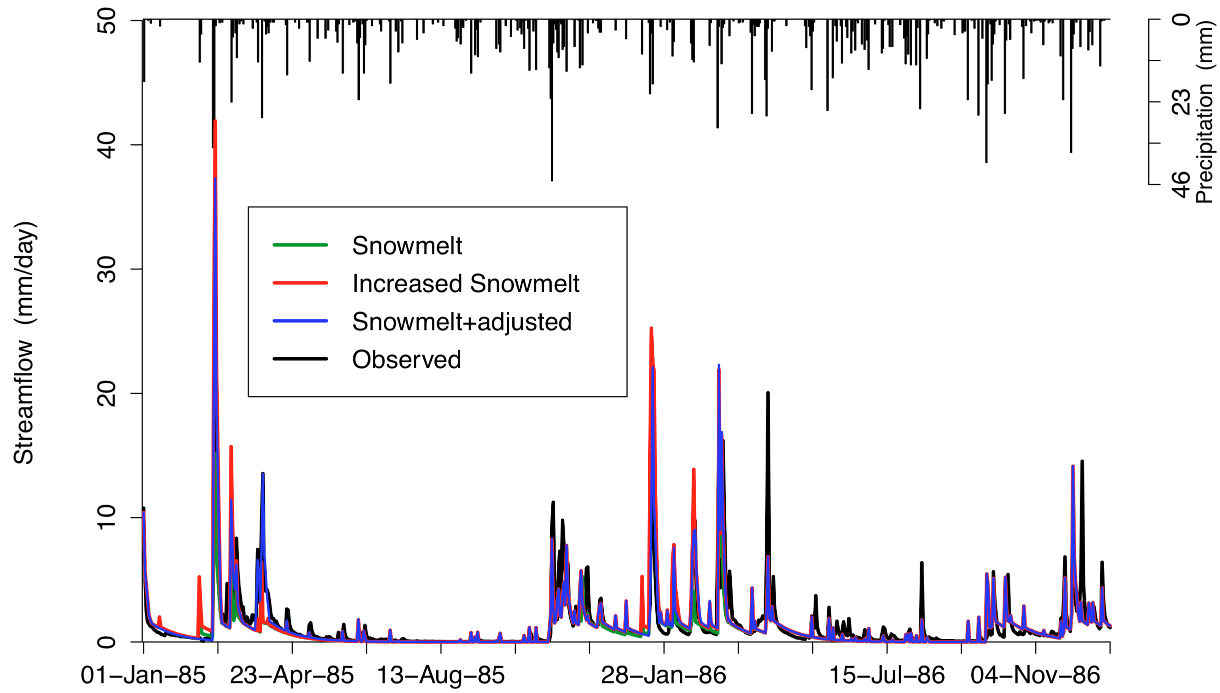
A. 6 SWAT Black Creek hydrographs for all calibration years



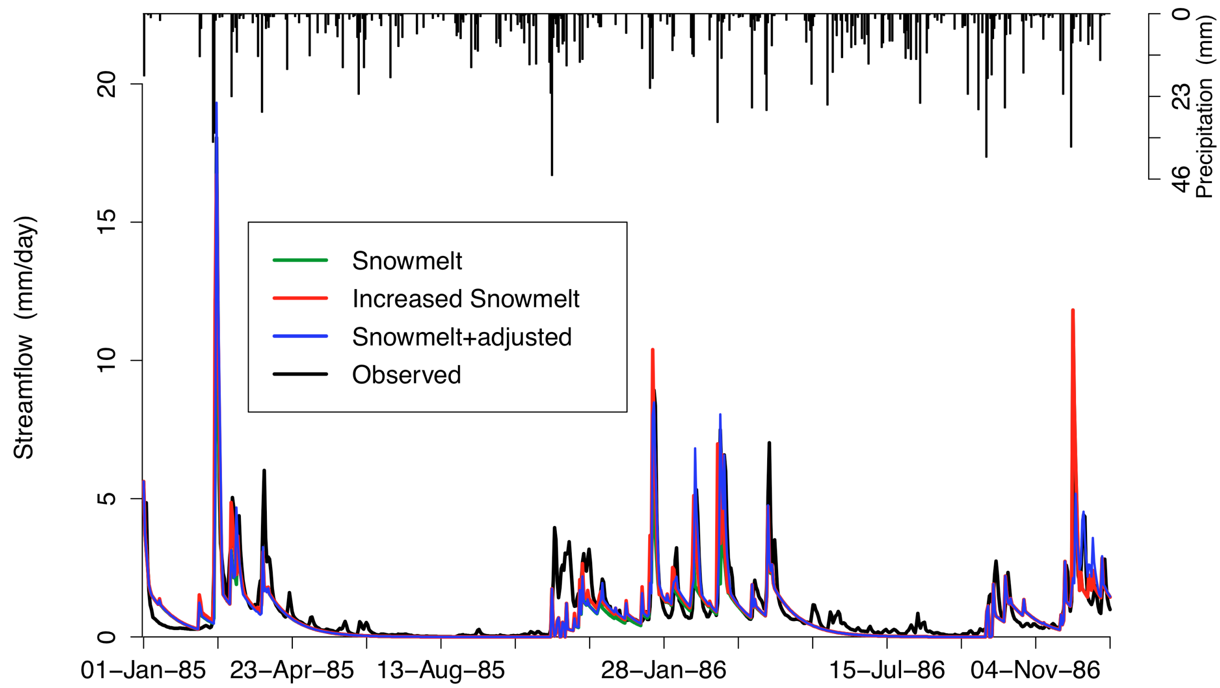
A. 7 PED Black Creek hydrograph for 1982



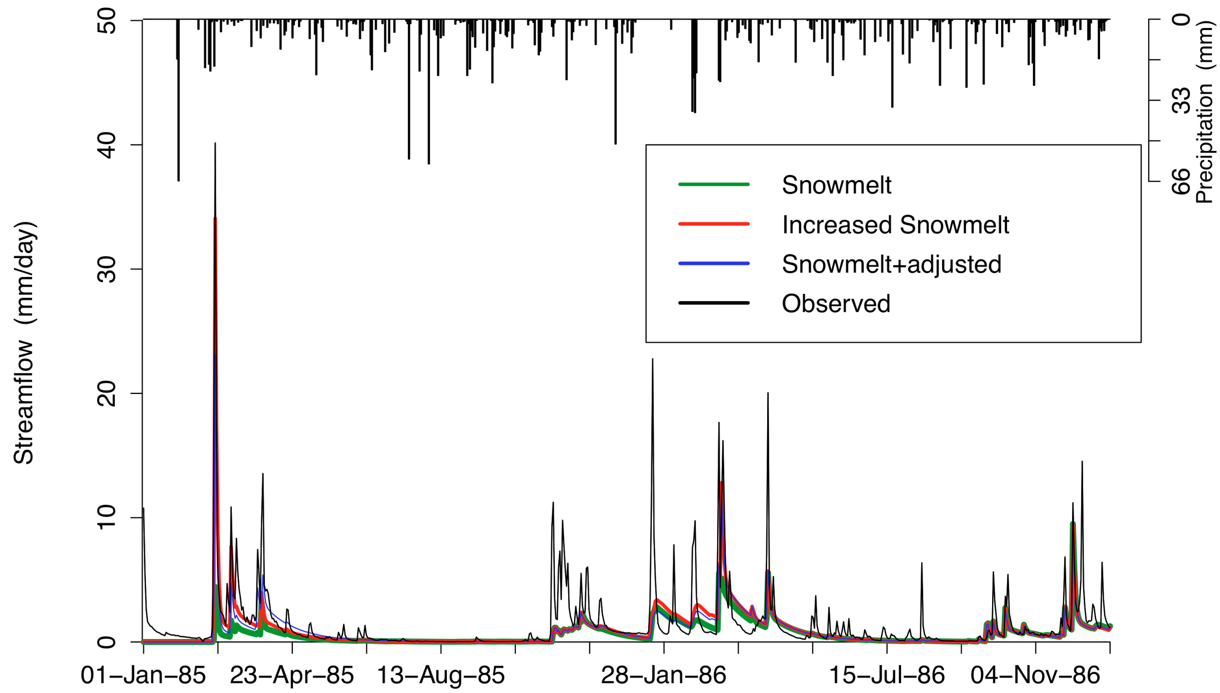
A. 8 PED Black Creek hydrograph for all calibration years



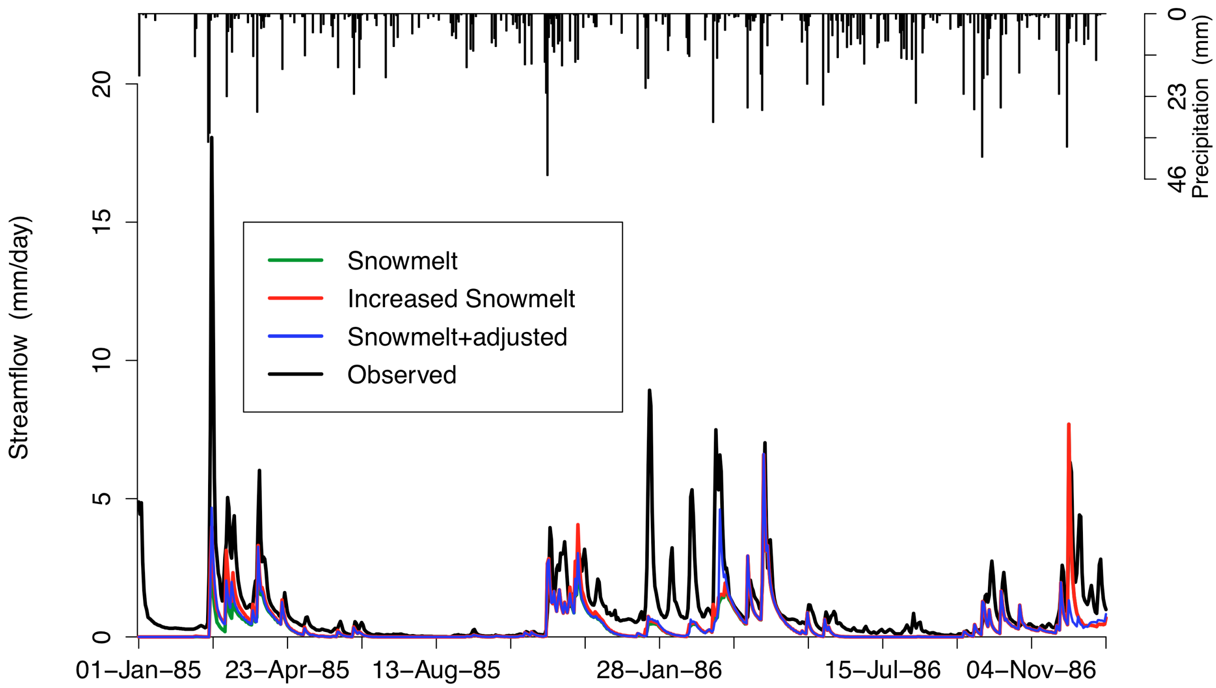
A. 9 Little Tonawanda PED all years for validation



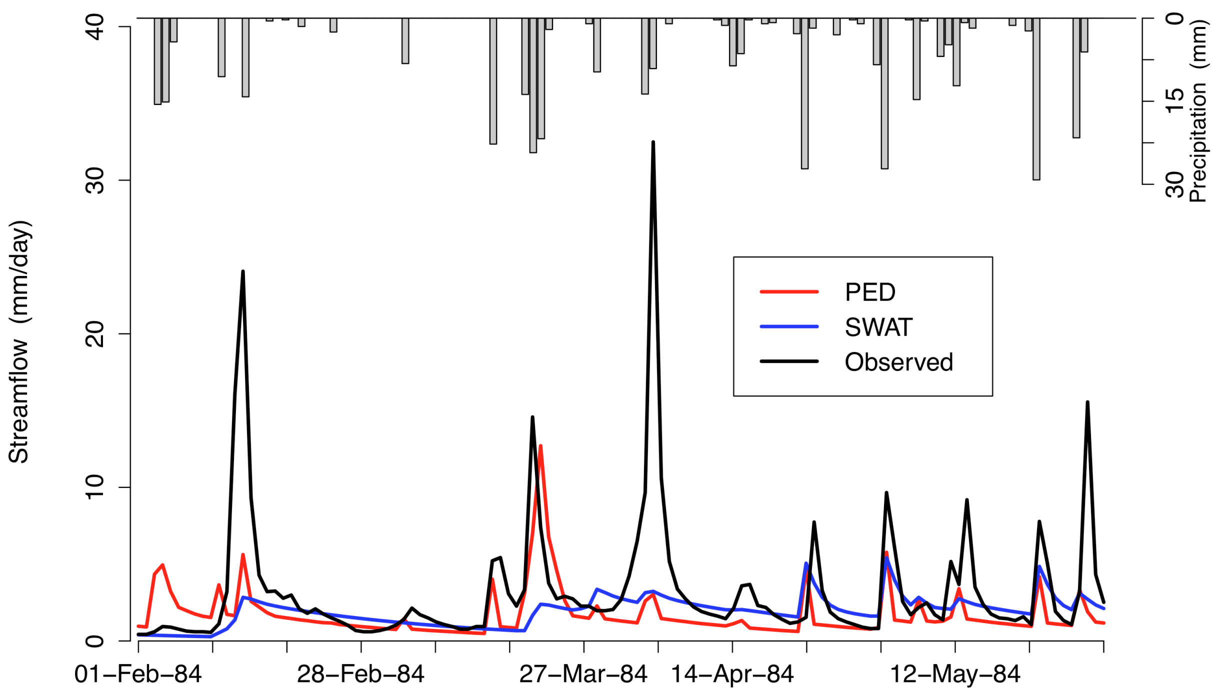
A. 10 Black Creek PED all years of validation period



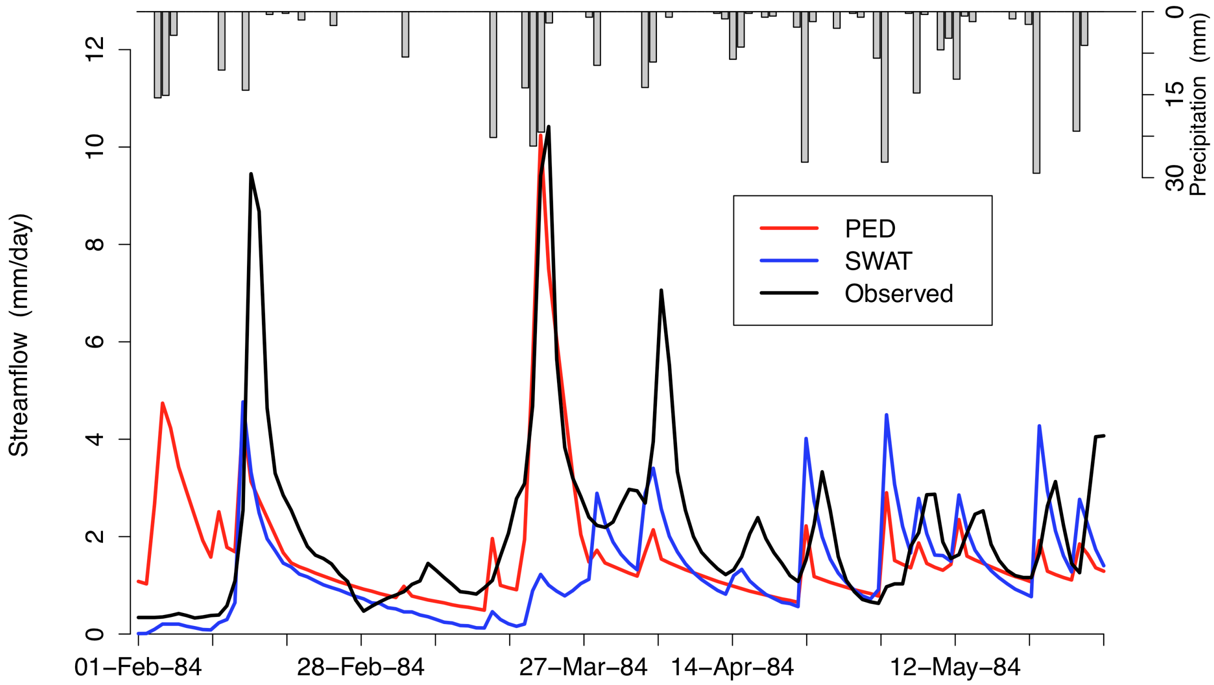
A. 11 SWAT Little Tonawanda validation for all years



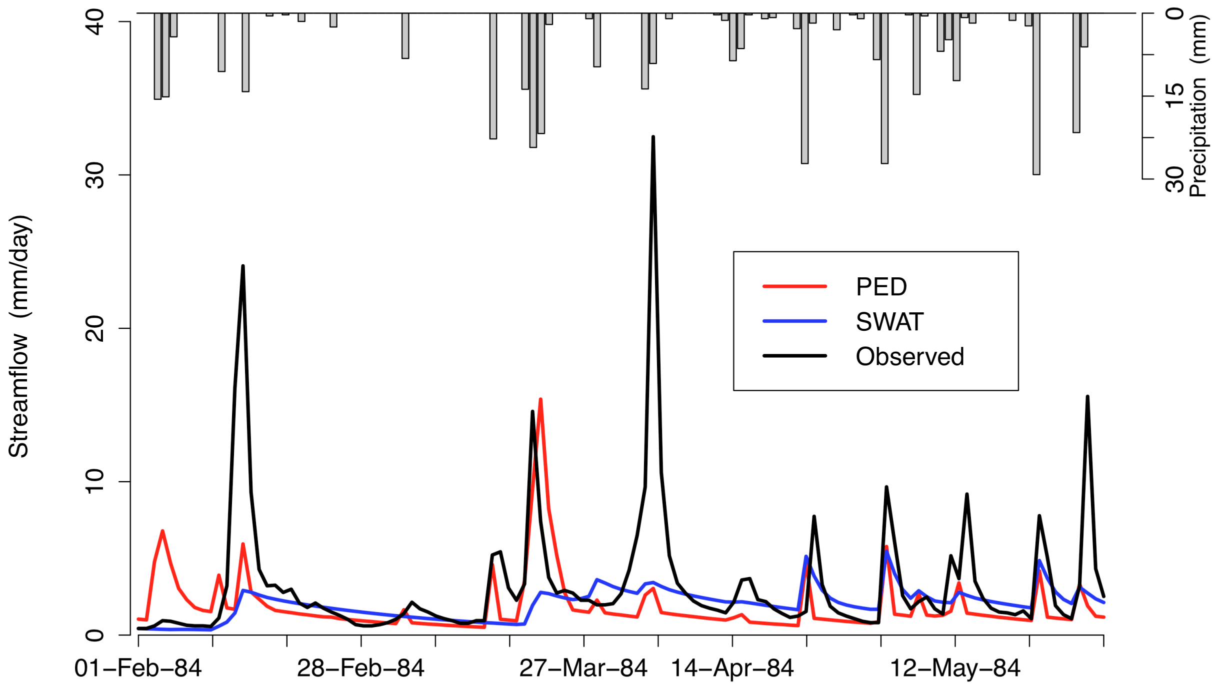
A. 12 SWAT Black Creek validation for all years



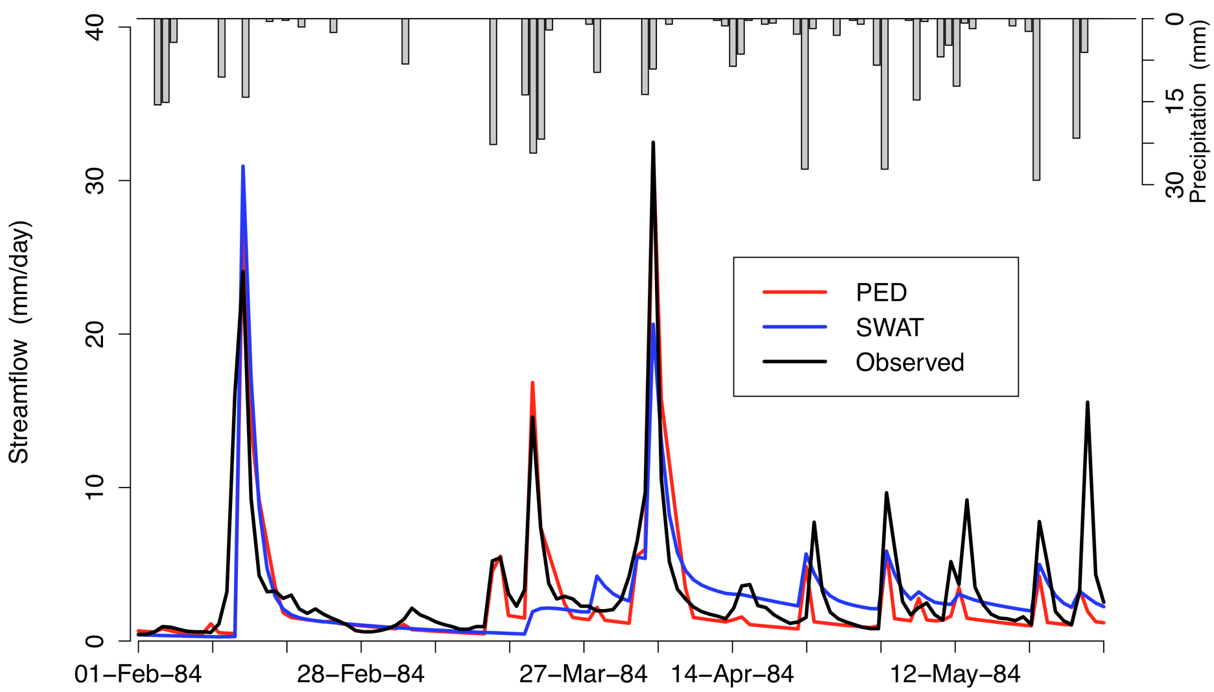
A. 13 SWAT and PED models for Little Tonawanda using the snowmelt dataset for winter 1984



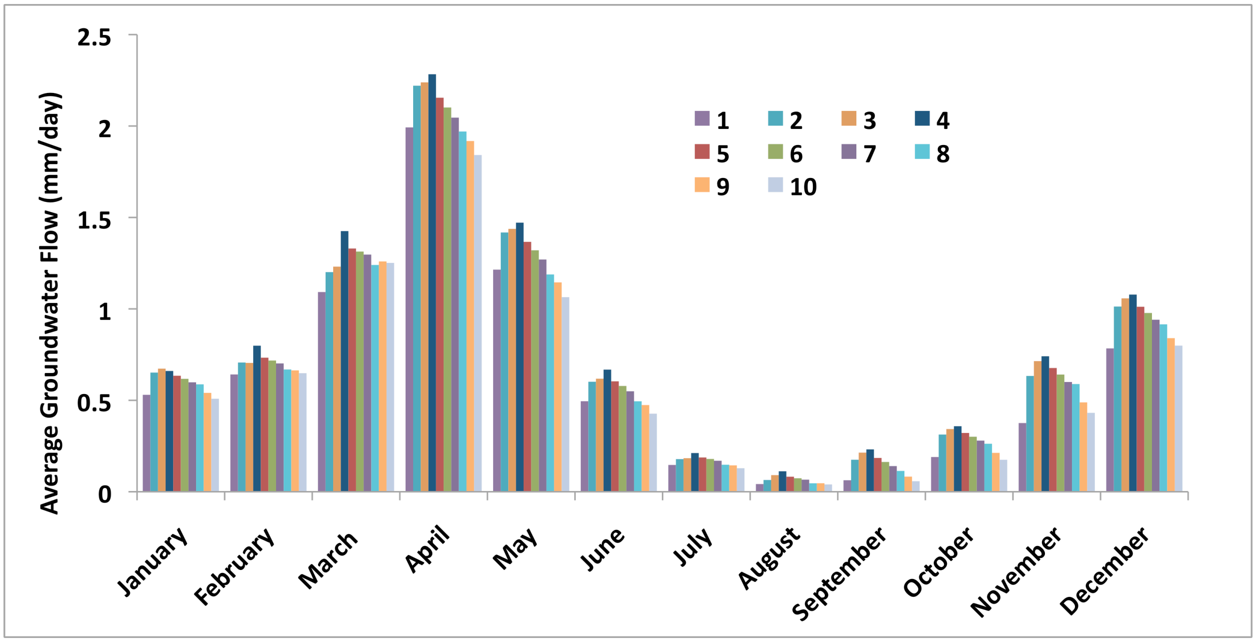
A. 14 SWAT and PED for Black Creek simulated with the snowmelt dataset for winter 1984.



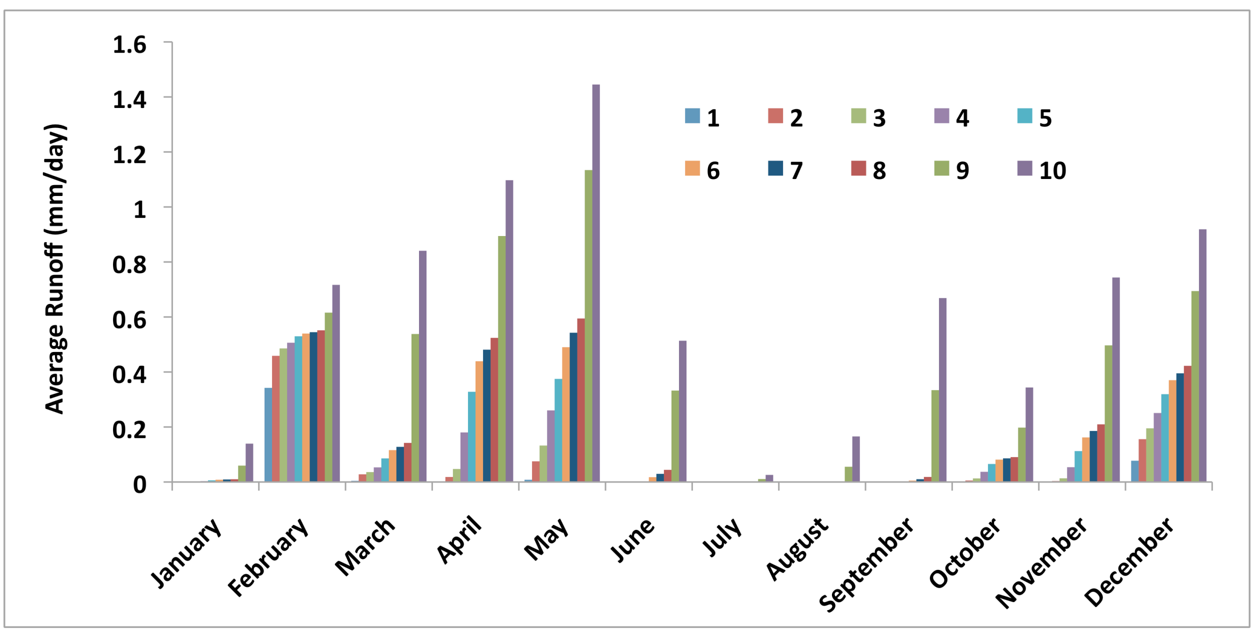
A. 15 SWAT and PED for Little Tonawanda simulated with the increased snowmelt dataset for winter 1984.



A. 16 SWAT and PED models for Little Tonawanda using the snowmelt+adjusted dataset for winter 1984.



A. 17 Little Tonawanda average monthly groundwater flow for each TI class. 1 is driest, 10 is wettest



A. 18 Black Creek average monthly runoff for each TI class. 1 is driest, 10 is wettest

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